A Review of Risk Analysis Research for the Operation of Autonomous Underwater Vehicles (AUVs)

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Abstract: Risk analysis for autonomous underwater vehicles (AUVs) aims to assist decision making for their safer operation. This article provides a structured review of risk analysis research to enhance the safety performance of AUVs. It aims to provide AUV stakeholders comprehensive insights into fundamental concepts and an evolution of analysis methods implemented for AUV operations. At the same time, it is expected to highlight future directions to bridge existing gaps. Forty-four articles with significant relevance to the scope of the work were retrieved and analyzed. Critical risk factors were identified and categorized. A comparatively analysis was undertaken from qualitative, semi-quantitative, and quantitative aspects. The study observes that as AUV technologies gradually mature, environmental factors, human factors, and their interactive impacts are gathering more attention. Quantitative risk analysis methods have recently played a key role in improving the accuracy and handling the uncertainties of risk estimation. The study recommends devoting efforts to dynamic risk analysis, addressing scarce historical data, intelligent risk analysis, and multi-vehicle risk analysis for future works.

Keywords: Autonomous underwater vehicles; Risk analysis; Risk factors; Marine safety; AUV safety; Literature review

1. Introduction

Autonomous Underwater Vehicles (AUVs) are effective platforms for navigating underwater or under ice to provide automated measurements without human intervention (Xu et al., 2013; Brito and Griffiths, 2016). The high level of autonomy of AUVs makes them an ideal tool for multiple data-gathering applications in scientific (Wadhams et al., 2006; Dowdeswell et al., 2008; Jenkins et al., 2010), commercial (Kleiner et al., 2011), military (Rothrock and Wensnahan, 2007), and geopolitical (Brito et al., 2012) areas. In recent research, AUVs are increasingly deployed in harsh environments such as under sea ice or ice shelves in the Antarctic (Nicholls et al., 2006; Jenkins et al., 2010; Cadena, 2011; Williams et al., 2015; Gwyther et al., 2020) and the Arctic (Wadhams et al., 2006; Dowdeswell et al., 2008; Salavasidis et al., 2016) regions. Operating in such extreme conditions, including thick ice cover, permafrost, fragile material integrity, unpredictable climatic changes, and poor visibility, will inevitably pose a higher risk to both the physical vehicle and the onsite AUV supervisors compared to open water missions (Loh et al., 2020c). Hence, it is essential to conduct effective risk analysis before a mission to ensure the safe deployment of AUVs.

Table 1 summarizes potential accidents and their severity of AUV operations, where AUV loss could be regarded as the most severe. AUV loss usually refers to the complete loss of the physical vehicle or an AUV being damaged and unrepairable for future missions. It is not only financially costly due to the higher insurance premium and acquisition costs of the vehicle (Griffiths et al., 2007a). Furthermore, it may also cause time delays or even the termination of research projects, lead to the loss of valuable gathered data, and potentially harm fragile polar environments (Griffiths and Collins, 2007; Brito et al., 2010).

Over the years, there have been a number of formally reported accidents of AUV losses during deployment, as shown in Fig. 1. For example, the AUV Autosub2 was lost under the Fimbulisen ice shelf in Antarctica on 16 February 2005. A formal accident inquiry concluded that this accident was equally likely to have been caused by an abort command or a loss of power. These technical failures was most likely introduced during the manufacturing and assembly phases (Strutt, 2006). Another lost vehicle, SeaBED, which was designed to scan the seafloor below overhanging sea ice, became trapped under the Antarctic ice during a mission and was almost crushed by an iceberg before it was rescued (Waters, 2015). The Autonomous Benthic Explorer (ABE) was lost on 5 March 2010, during its 222nd research dive off the coast of Chile. Researchers believed that the loss of the ABE was also caused by a technical failure. More specifically, the ABE may have suffered a catastrophic implosion of a glass sphere used for providing buoyancy, causing instant destruction of the on-board systems. Consequently, the ABE failed to send fail-safe commands for helping itself float to the surface for recovery (Lippsett, 2010). An underwater glider, Seaglider SG522, lost communication in the Antarctic on 14 February 2012 after having completed 156 dives. The inquiry panel identified that the root cause was an erroneous command, which resulted in this glider continuously diving and eventually being lost. (Brito et al., 2014b). On 4 April 2014, the Autosub Long Range AUV lost communication during a mission near the Irish coast. Luckily, it re-transmitted its position signal and was recovered after three months. More recently, a Hugin AUV was lost during its first under ice mission in the Antarctic on 15 January 2019, and was recovered four days later. Pre-dive checks had been reviewed for this vehicle without any irregularities. Technicians believed the vehicle was trapped below an ice floe, causing the Iridium signal for the AUV position failing to be received (Bound, 2019).

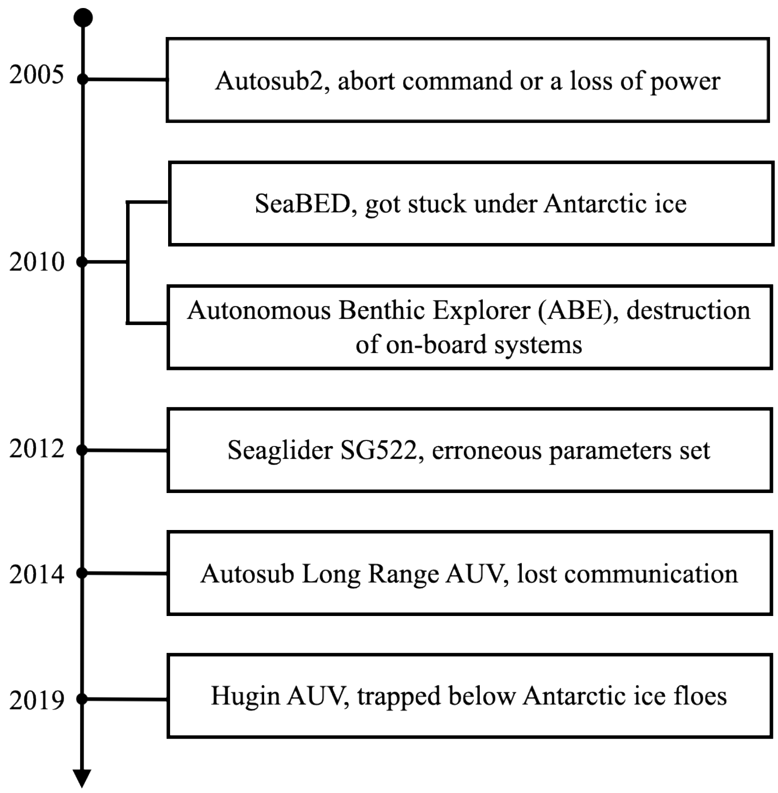


Fig. 1. Timeline and potential causes of historical accidents of AUV loss.

Table 1. Classification of the consequence severity of AUV operations.

Level	Consequence	Severity
I	AUV loss	Catastrophic
II	Severe damage, mission failure, mission abort	Critical
III	Mitigable damage, mission degraded, mission delayed	Moderate
IV	Minor damage	Marginal
V	Minimal damage or no damage	Negligible

From the overview of historical accidents of AUV loss, it is observed that the potential causes of historical accidents show a wide variety, which confirms the unpredictable and uncertain features of AUV related accidents. This non-uniform accidental pattern as well as relatively severe consequences imply the vulnerability of AUV operations and reinforce the necessity of implementing effective risk analysis before an AUV mission.

Risk analysis is a proactive approach for hazard identification, consequence analysis, and risk estimation for potential accidents (Rausand, 2013). As AUV technologies have gradually matured, risk analysis for AUV operations has rapidly become important to assist decision making and provide preventive risk mitigating measures. A number of past efforts regarding risk analysis research have been undertaken to improve the safety performance of AUVs. However, to the best knowledge of the authors, a systematic review and analysis of previous research has not yet been done. As a thorough review will enable domain researchers to gain better understanding of AUV risk analysis and benefit future development, the authors believe that a critical review article is timely.

In light of the above, the objective of this article is to provide a structured review of risk analysis research regarding AUV operations. It aims to answer several key questions arising from historical developments and to predict future trends in this domain, as listed in Table 2. The main contribution of this study is to help researchers and AUV stakeholders obtain comprehensive insights about fundamental concepts and major methodologies for the risk analysis of AUVs, and to indicate directions for future research to bridge existing gaps.

Table 2. Research questions regarding previous studies of AUV risk analysis.

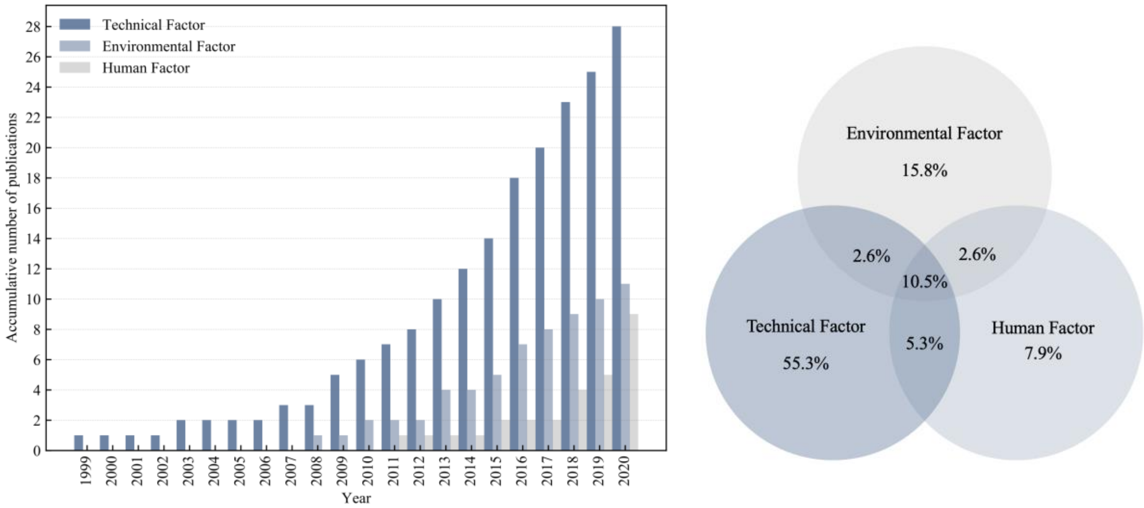
Question	**Description**	**Section**
Q_1	What is risk analysis for AUV operations?	Section 1
Q_2	Why implement risk analysis for AUV operations?	Section 1
Q_3	How is risk analysis implemented for AUV operations?	Section 2&3
	$Q_{3,1}$: What are the key risk factors identified in past studies?	Section 2
	$Q_{3,2}$: Which risk analysis method was adopted in past studies?	Section 3
	$Q_{3,3}$: What are the advantages and disadvantages of these methods?	Section 3
	$Q_{3,4}$: What trends can be observed regarding past studies?	Section 2&3
Q_4	What are the future challenges of risk analysis for AUV operations?	Section 4

The scope of this study is restricted to research which is closely related to risk analysis for AUV operations. According to the objective and scope of this review, the literature retrieval was performed based on keywords including AUVs with the combination of risk identification, risk analysis, risk assessment, risk management, risk mitigation, risk modeling, and safety measures. A total of forty-four articles with significant relevance to the research purpose and scope were retrieved. In addition, in order to better answer the research questions and facilitate further statistical analysis, the selected publications were classified into various aspects, such as the type of identified risk factors, the type of adopted risk analysis methods, the type of mission forms, the area of operations, and the type of potential consequences. The dataset of selected literature is classified and summarized in the Appendix.

The article is structured as follows. In section 2, critical risk factors of AUV operations are identified and summarized by categorizing them into technical factors, environmental factors, and human factors. Section 3 compares adopted risk analysis methods for AUV operations by classifying them as three types: qualitative methods, semi-quantitative methods, and quantitative methods. Section 4 briefly outlines current research gaps and future directions. The summary and conclusion of this study are given in Section 5.

2. Risk factors identification of the AUV operations

Risk identification is defined as the process of identifying potential risk factors, which is the first step of the risk analysis phases (Rausand, 2013). By reviewing the chosen literature, identified risk factors related to AUVs are summarized in this section by categorizing them into technical factors, human factors, and environmental factors. Fig. 2 illustrates the distribution of the number of publications regarding the three types of risk factors. It is observed that research of technical factors has been steadily increasing over the last two decades and now surpasses the other two factors. By contrast, research on human factors, environmental factors, and the interactive factors is emerging in recent years and receiving more attention. Each of the three risk factors is elaborated in the following subsections.



(a) (b)

Fig. 2. Distribution of the research of three risk factors regarding (a) the accumulative number of publications and (b) the proportion of the publications.

2.1 Technical factor analysis of AUV operations

A technical factor is defined as a risk contributor that is directly related to the AUV technical systems and components (Hegde et al., 2018). Previous studies have primarily focused on improving the technical performance of AUVs. As shown in Fig. 2, the number of studies related to technical factors account for 55.3% of the domain publications. It is important to understand the difference between a failure, fault, and error. A failure refers to the inability of a component or system to perform a required function. A fault is defined as an abnormal condition, state, or defect, which may lead to a failure. An error refers to the discrepancy between a value, condition, or human behavior. It usually occurs when deviating from the target performance, which can also cause a failure (Rausand and Høyland, 2003). With complex subsystems and components of an AUV, a technical failure can easily occur with electromechanical equipment, and then cause functional failures of a certain subsystem. Since AUVs operate mainly depending on the cooperation of their subsystems without human intervention. Once a subsystem fails to work, there is a high risk of overall mission failure. In particular, as a self-contained submarine robot, there is limited scope for calibrating and testing each component or subsystem thoroughly before a mission.

Therefore, technical factors are most fundamental and paramount for safe deployment of AUVs.

In order to better identify technical factors of AUVs, it is important to understand the main functions of AUV subsystems and key components, which are summarized in Table 3. The major subsystems of an AUV consist of the propulsion system, navigation system, communication system, energy system, security detection system, sensor system, and others. A propulsion system is responsible for providing the propulsive force and, in the case of gliders, to change the buoyancy. In general, AUVs can be classified into two types according to their different propulsion systems. The first type is actively-propelled AUVs with traditional propellers or thrusters to empower propulsion behavior, including horizontal and vertical movement. Another type is passively-propelled AUVs, such as underwater gliders, which employ variable-buoyancy propulsion without any propeller type thrusters. Gliders can ascend and descend underwater through control by a buoyancy changing system. Simultaneously, they use wings to convert the vertical motion into horizontal motion, thereby achieving a sawtooth pathway in the water column. A navigation system enables an AUV to follow a predefined trajectory by measuring its position, attitude, and velocity. Among several kinds of navigations systems of AUVs, the inertial navigation system (INS) is a widely used navigation system. The INS typically contains an inertial measurement unit (IMU) including accelerometers and gyroscopes. For inertial navigation, the linear acceleration is measured by accelerometers and the angular velocity is measured by gyroscopes, and these parameters are combined to calculate the instantaneous velocity and position of the vehicle (Paull et al., 2014; Bao et al., 2020). In addition, some aided components, such as a Doppler Velocity Log (DVL), compass, pressure sensor, or global positioning system (GPS), are usually combined with the INS to provide integrated navigation. Among these auxiliary components, a DVL is an acoustic sensor that measures the velocity and position of the vehicle relative to the sea bottom; a compass is used for orientation that provides the heading direction for the vehicle; a pressure sensor is used to measure the external pressure of the vehicle, from which the water depth can be estimated; GPS is a satellite-based positioning system, which enables an AUV near the water surface to acquire its position information, and GPS signals are input to the INS to correct the position measurement. A communication system is used for transferring and controlling the mission instructions, and it is particularly crucial during multi-vehicle missions. This system includes two parts: underwater communication is achieved by an acoustic modem, and above-water communication is achieved by local radio communication with an antenna. An energy system provides electrical energy which uses lithium-ion batteries or alkaline batteries (Griffiths et al., 2007b). Former studies have proved that more than 50% of AUV loss accidents are related to a power failure (Meng and Qingyu, 2010; Yu et al., 2017). An early study analyzed 63 mission abort incidents from a total of 205 glider missions (Brito et al., 2014a). As shown in Fig. 3, among the identified 19 failure modes of gliders, power failure was ranked as the second most common failure mode. Since the energy system powers all electrical motors, sensors, and the central computer, it is critical for the normal functioning of AUVs. In addition, it decides the mission endurance, which is influenced by the available energy storage and the energy consumption rate. An environmental detection system generally processes sensor data to perceive the surrounding environment, detects the forward obstacles, and prevents the AUVs from colliding with the seafloor. An emergency system ensures safety in emergency situations. Its overrides the navigation system by employing the low-risk path planning during the collision avoidance maneuver (Hegde et al., 2018). In addition, it also predominates the propulsion system in dangerous situations. For example, it can provide fail-safe measures by releasing the drop-weight, aborting the mission, and floating the vehicle to the water surface for rescue.

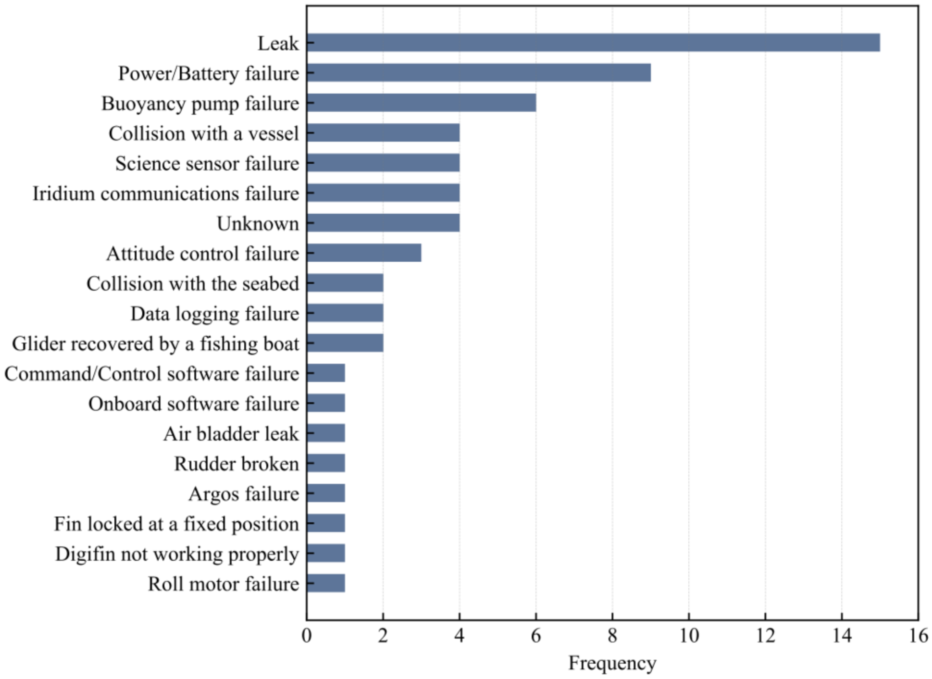


Fig. 3. Failure modes and their frequency during 63 abort incidents from 205 glider missions (Brito et al., 2014a).

There are various strategies to improve the technical performance of an AUV. Redundancies of key components can be provided for the hardware level (Yu et al., 2017). For example, installation of a backup battery can significantly reduce the probability of energy system failure. For the software level, online monitoring and repairing could serve as effective risk mitigation measures (Aslansefat et al., 2014). In addition, as a majority of failures occur in the early phase of a mission, an endurance test can be performed in the operational configuration to monitor key subsystems before a mission (Kaminski et al., 2010). A mission can then proceed only when the vehicle operates properly during the endurance test. Otherwise, the vehicle should be recovered for onboard fault checking.

Table 3. Identification of AUV subsystems and risk factors.

AUV Subsystem	Functionality	Main Component	Risk Factor	Reference
Propulsion System	• Provide the propulsive force • Change the buoyancy	Propeller or thruster (active-propelled AUV) Variable-buoyancy system (passive-propelled AUV)	Thruster failure Buoyancy pump failure Bladder leak Fin actuator failure Rudder broken	(Stevenson and Hunter, 1994; Griffiths et al., 2003; Bian et al., 2009a, b; Xu et al., 2013; Aslansefat et al., 2014; Yu et al., 2017; Hegde et al., 2018)
Navigation System	• Measure the position, attitude, and velocity data • Provide dead-reckoning navigation • Follow the predefined trajectory	DVL On-board GPS receiver Attitude sensor Depth sensor Altimeter	DVL failure Depth sensor failure Altimeter failure Inertial navigation failure GPS module failure	(McPhail, 1993; McPhail, 1998; Griffiths et al., 2003; Bian et al., 2009a, b; Xu et al., 2013; Aslansefat et al., 2014; Yu et al., 2017; Hegde et al., 2018)
Communication System	• Underwater communication • Above water communication • Transfer and control the mission instruction	Acoustic sensor Radio transceiver module	Underwater acoustic sensor failure Radio communication failure Signal transmission failure Host computer failure	(Meldrum and Haddrell, 1994; Bian et al., 2009a, b; Aslansefat et al., 2014; Brito et al., 2014b; Yu et al., 2017; Hegde et al., 2018)
Energy System	• Provide electrical energy	Lithium-ion battery Alkaline battery	Energy depletion Fail to charge Overcharging Battery detection failure	(Winchester et al., 2002; Bian et al., 2009a, b; Xu et al., 2013; Aslansefat et al., 2014; Yu et al., 2017; Hegde et al., 2018)

			Voltage and current monitoring failure	
Environmental Detection System	• Perceive the surrounding environment • Avoid the forward obstacles • Prevent colliding with the seafloor	Camera Forward-looking sonar CTD sensor	Underwater camera failure Light sources failure Sonar suite failure CTD failure	(Bian et al., 2009a, b; Xu et al., 2013; Aslansefat et al., 2014; Yu et al., 2017; Hegde et al., 2018)
Emergency System	• Ensure safety in an emergency situation • Alternate the low-risk path planning • Jettison weight for fail-safe	Drop-weight	Hermetic hull broken Leak detection sensor failure Jettison device failure Mission aborting command failure	(Ortiz et al., 1999; Bian et al., 2009a, b; Xu et al., 2013; Yu et al., 2017; Hegde et al., 2018)

2.2 Human factor analysis of AUV operations

The maturing of AUV technologies has fostered a gradual shift to risk analysis of human operators. To comprehensively control the risk of AUV deployments, human factors, which are critical but relatively difficult to quantify, are receiving more attention in the AUV risk management process. Human intervention influences autonomy of AUVs. Autonomy is defined as the capability of a system to make decisions independently, which can be measured in six levels, namely (i) human operated, (ii) human assisted, (iii) human delegated, (iv) human supervised, (v) mixed initiative, and (iv) fully autonomous (NFA, 2012; Thieme et al., 2015b). The level of autonomy denotes involvement of human operators, i.e., a higher level of autonomy refers to less human intervention. Current AUV systems can be categorized into level (ii), (iii), and (iv), while future AUVs may reach level (v) and level (vi). Therefore, although an AUV system in the current state has a certain level of autonomy, human operators still play a vital role as a supervisor. The main intervention of human operators includes determining mission plans in the design phase, performing the launch and recovery of the vehicle, taking control when encountering emergencies, and so on (Henriksen et al., 2016; Loh et al., 2020c). Errors caused by human involvement may lead to the AUV being susceptible to failure. During the four-year missions of the Autosub3 AUV from 1996 to 2000, the most faults were notably identified as a result of human errors rather than technical failures, as shown in Fig. 4 (Griffiths et al., 2003).

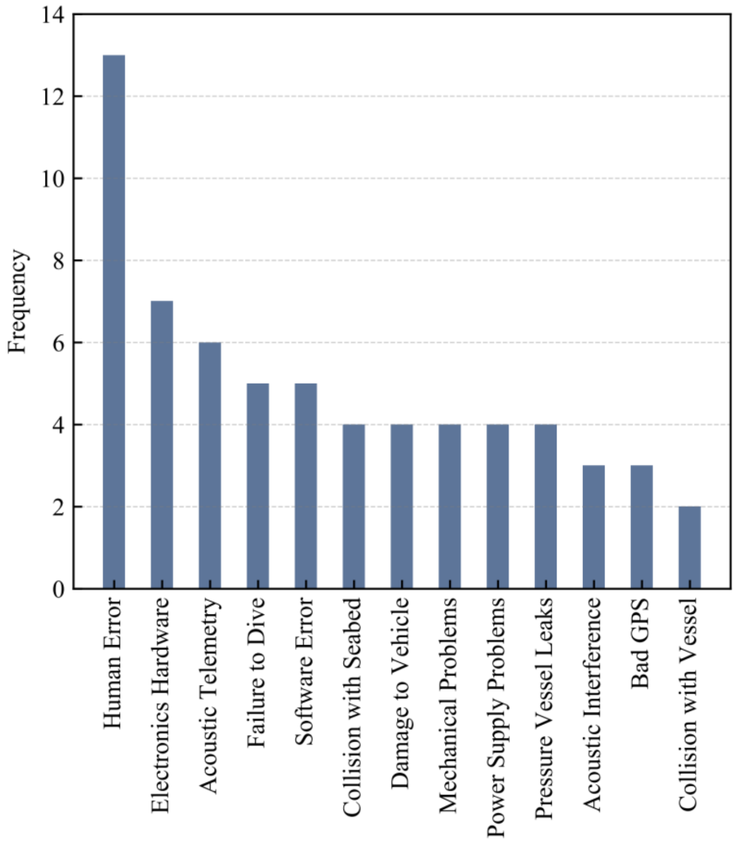


Fig. 4. Failure modes and their frequency during missions 1-240 of the Autosub3 AUV from 1996 to 2000 (Griffiths et al., 2003).

Researchers have begun to recognize the importance of human factors contributing to the overall risk of AUV operation (Stokey et al., 1999; Manley, 2007; Ho et al., 2011; Akhtar and Utne, 2014). A risk management framework incorporating human and organizational factors was established (Thieme et al., 2015a). This study proposed a structured approach to assess the risk of AUV loss and mission aborts resulting from human factors. Potential risk mitigation measures were provided, such as procedures improvement, mission planning, and fault recognition. A case study involving the operation of the REMUS 100 AUV was conducted, which proved that risk analysis should not only consider the technical system itself but also emphasize the human interaction with the system. Extended studies assessed human factors in risk monitoring of AUV missions (Thieme et al., 2015b; Hegde et al., 2018). Detailed information of human factors, such as level of training, operator experience, operator fatigue, and situation awareness, were analyzed in these studies. Furthermore, a system-based risk analysis framework was proposed for an in-depth analysis of the impact of human factors (Loh et al., 2019; Loh et al., 2020a; Loh et al., 2020b; Xu et al., 2020). Several key findings were demonstrated by these studies. The risk level of AUV loss will gradually drop in the initial years of the formation of an AUV team, reaching a minimal level before rising again in later periods. In addition, the human error incident rate was proven to decline with the overall increase of the experience of an AUV team. Therefore, increasing the experience of an AUV operator can be an effective measure of risk reduction, which can be achieved by safety training, human resources allocation, recruitment, and staff retention. Human factors identified in previous studies are summarized in Table 4.

Table 4. Identified human factors in previous literature.

Human Factor	Description	Reference
Supervisory error checking	Ability of the operator to timely identify errors and contingency situations during a mission.	(Loh et al., 2020c)
Supervisory handling	Ability of the human supervisor to take required actions.	(Hegde et al., 2018; Loh et al., 2020c)
Wrong configuration setting	Wrong configuration parameters of a sensor are set which might lead to incorrect measurement.	(Loh et al., 2020c)
Workload	Number of tasks that the operators are required to execute.	(Parasuraman and Miller, 2004; Ho et al., 2011; Fouse et al., 2012; Thieme et al., 2015b)
Experience of operators	Level of experience of the operators with the deployment mission.	(Manley, 2007; Loh et al., 2020a; Loh et al., 2020c, b)
Human fatigue	Inability to function at the desired level due to incomplete recovery from the demands of prior work and other working activities.	(Akhtar and Utne, 2014; Loh et al., 2020c)
Training of operators	Level of required operational and safety training for a human supervisor.	(Thieme et al., 2015b; Hegde et al., 2018)
Situational awareness	Ability to monitor the system, comprehend the information and take the right decisions.	(Baxter and Bass, 1998; Ho et al., 2011; Johnson and Lane, 2011)

Communication of operators	Level of communication effectiveness among operators and the crew.	(Thieme et al., 2015b)
Trust in the system	Level of the operator's belief in the autonomous capabilities of the AUV.	(Parasuraman and Miller, 2004; Johnson et al., 2007; Ho et al., 2011)

2.3 Environmental factor analysis of AUV operations

AUVs operate in several typical subsea environments such as under open water (Brito et al., 2014a) (Brito et al., 2008), under sea ice or shelf ice (Griffiths and Brito, 2008; Brito and Griffiths, 2016) (McPhail et al., 2009), and along coastal areas (An et al., 2001; Koay and Chitre, 2013; Oliver et al., 2013), as shown in Fig.5. Due to the dynamic and hazardous nature of subsea environments, safe deployment of AUVs is challenging. Therefore, it is vital to identify underwater environmental factors and comprehend how they cause risk to AUV operations. Based on former studies, this section has analyzed four critical risk-related environmental factors, including sea ice, underwater currents, ambient temperature, and water density.

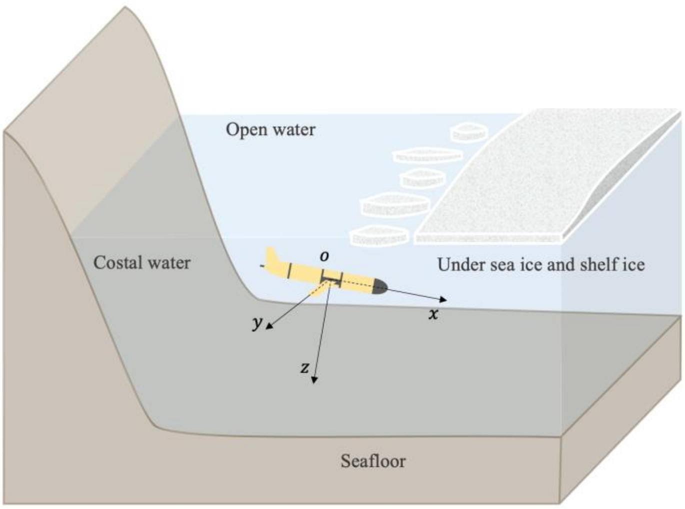


Fig. 5. Typical operating environments of AUVs.

2.3.1 Sea ice

Deploying an AUV in the polar regions has a higher risk than in other areas, and sea ice is as a critical contributor. For example, a former study proved that the median probabilities of AUV loss in under sea-ice and under ice-shelf missions are 4.9 and 9.4 times higher than in open water missions (Brito et al., 2010).

Sea ice, which is characterized by ice thickness and ice concentration, can affect the AUVs operational risk in multiple ways. Firstly, sea ice with modest thickness may pose a collision risk and poor visibility in the recovery phase or the fail-safe phase, as it could form a rigid lid and lead to the AUV being trapped under the ice when floating to the surface. Moreover, it may damage components such as the antennas and propeller blades during the floating process or crack the vehicle hull and cause leakage. Secondly, the occurrence probability of these collision incidents will increase with ice concentration. Finally, the communication efficiency can be affected by both ice thickness and concentration (Brito and Griffiths, 2016). The ability to receive satellite signals will be compromised under ice, and poor communication increases the difficulties for vehicle relocation.

To prevent collision with ice, risk mitigation measures can be taken, such as attaching a tether to the vehicle (Doble et al., 2009; Forrest et al., 2012), mounting a locating beacon inside the vehicle (Kukulya et al., 2010), temporarily parking the vehicle in a safe location (Ferguson, 2008; Kaminski et al., 2010), and optimizing the obstacle avoidance system (Pebody, 2008; Eichhorn, 2009).

2.3.2 Underwater current

Underwater currents result from the surface winds, gravitational tides, water density, and water pressure at a certain depth (Hegde et al., 2018; Ullah et al., 2020). Underwater currents are a critical issue for the dynamic motion control of AUVs, especially for the relatively slow-moving underwater gliders with a typical velocity below 0.5 m/s (Griffiths et al., 2007b; Petillo and Schmidt, 2012). Without external thrusters, a glider is easily subjected to environmental disturbances (e.g., strong currents). For example, strong currents may deviate its predefined path, and as a result, a glider cannot reach its target position.

Various strategies have been proposed to improve AUV control against underwater currents, such as increasing the surfacing frequency to reduce positioning errors resulting from the currents (Bachmayer et al., 2006) and optimizing the navigation system by integrating current models (Smith et al., 2012; Von Oppeln-Bronikowski et al., 2020).

2.3.3 Ambient temperature

Another key environmental factor which may cause danger for AUV operations is the ambient temperature. Low ambient temperature especially in polar regions, can cause large temperature gradients between the air and the water column. Consequently, the vehicle or component may suffer integrity failure and leakage (Ferguson, 2008). For instance, it has been known for the seal of a CTD sensor to crack at low ambient temperatures, and therefore sea water can penetrate and freeze inside, and eventually cause sensor failure (Kaminski et al., 2010). Additionally, low temperature also forces ice formation on the equipment. One example found that the GPS of an AUV was unable to acquire satellite signals when working in the Arctic, possibly due to a thin layer of ice which formed on the antenna (Bellingham et al., 2008). Another potential challenge caused by low temperature is the degradation of the energy system. As introduced in Section 3.1, lithium batteries are widely used as the energy source of AUVs. However, in cold environments, especially when the ambient temperature is below -20℃, the battery capacity may drop significantly. Therefore, poor battery performance could further lead to premature energy depletion and a mission abort (Bandhauer et al., 2011). Apart from the impact on the vehicle, low temperature will cause a harsh working condition for the AUV crew, both physically and psychologically.

2.3.4 Water density

As a factor of underwater thermohaline circulation, water density is decided by the combination of the water depth, water temperature, and salinity (Fofonoff and Millard

Jr, 1983). Water density has a critical influence on providing positive buoyancy of AUVs, according to Equation (1).

$$F_B = \rho_{seawater} g V_{total} \tag{1}$$

where F_B is the buoyant force in N, $\rho_{seawater}$ is the density of seawater in kg/m^3, V_{total} is the total volume of the vehicle and the external bladder in m^3, and g is the gravitational acceleration in m/s^2.

It is noted in Section 3.1 that some passively-propelled AUVs, such as underwater gliders, usually control their buoyancy either by filling an external bladder or by pushing seawater in or out of an internal reservoir (Griffiths et al., 2007b). However, in some areas, for instance, near melting glaciers, seawater density can change with a large gradient. As a result, decreasing water density due to salinity dilution would require supplementary buoyancy for the vehicle's rising motion (Bachmayer et al., 2006; Dowdeswell et al., 2008). On the contrary, in other areas where the water density is relatively high, redundant buoyancy could be provided and consequently compromises the vehicle's diving motion. In conclusion, once the water-density gradients exceed the compensating range of the vehicle, unstable buoyant control will occur, and the vehicle may become trapped in a neutrally buoyant water-layer and fail to float to the surface, or the vehicle is unable to dive to the planned depth. Thus, pre-measurement of the water density is necessary before an AUV mission to prevent buoyant control problems.

According to the above analysis, the impact of various subsea environmental factors and their interacting relationships are topologically represented in Fig. 6, where the arrows point to the functional failures caused by environmental factors. It is evident that distinct environmental factors may interact with each other and cause different functional failures. Hence, when conducting risk analysis of AUVs in a certain environment, the operator must be aware of this and update the environmental factors according to local configuration characteristics.

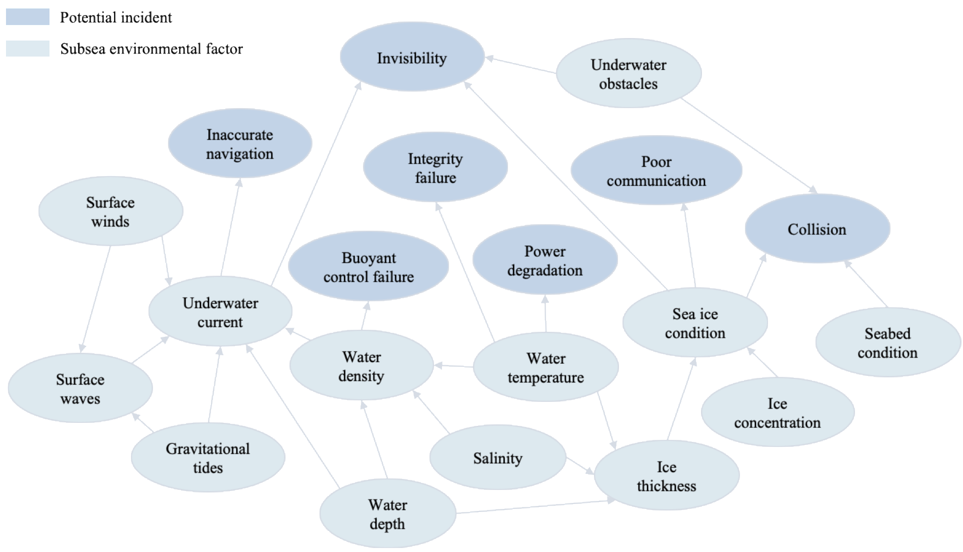


Fig. 6. Risk identification of subsea environmental factors.

3. Risk analysis methods of AUV operations

This section provides an overview of existing methods for risk analysis of AUV operations. It aims to outline the evolution of the developed methods and models, critically analyze the progress and limitations of past research, and highlight future research trends in this domain. This section is expected to help researchers gain better understanding of historical developments for AUV risk analysis methods and bridge the existing research gaps in future work. In this section, the reviewed methods are categorized into qualitative, semi-quantitative, and quantitative methods. The classification of main risk analysis methods regarding AUV operations is shown in Table 5. Related to the three types of methods, Fig. 7 shows the distribution of the number of publications in each area over the last two decades. It is observed that research using quantitative methods has rapidly increased in recent years, which implies that quantitative representation is becoming more widespread in risk analysis of AUVs. In the following subsections, typical methods relating to risk analysis of AUVs will be discussed.

Table 5. Classification of typical risk analysis methods regarding AUV operations.

Risk Analysis Method		Reference
Qualitative	Safety layer method	(Ortiz et al., 1999)

Semi-quantitative	Risk management process	(Griffiths and Trembanis, 2007; Brito et al., 2010; Griffiths and Brito, 2011; Thieme et al., 2015a)
	Fault tree analysis	(Bian et al., 2009a, b; Hu et al., 2013; Xu et al., 2013; Aslansefat et al., 2014; Thieme et al., 2015a; Brito, 2016; Harris et al., 2016; Xiang et al., 2017; Brito and Chang, 2018)
	Event tree analysis	(Thieme et al., 2015a; Brito et al., 2018)
	Failure Mode and Effects Analysis	(Hu et al., 2013; Harris et al., 2016)
	Bow-tie model	(Yu et al., 2017)
	Kaplan-Meier survival model	(Brito et al., 2010; Brito et al., 2014a; Brito and Griffiths, 2016)
	Fuzzy set theory	(Loh et al., 2019; Loh et al., 2020a; Loh et al., 2020b; Xu et al., 2020)
Quantitative	Bayesian belief network	(Griffiths and Brito, 2008; Brito et al., 2012; Thieme et al., 2015b; Brito and Griffiths, 2016; Brito and Griffiths, 2018; Hegde et al., 2018; Bremnes et al., 2019)
	Markov chain	(Brito and Griffiths, 2011; Griffiths and Brito, 2011)
	System dynamics	(Brito and Griffiths, 2012; Loh et al., 2020a; Loh et al., 2020c, b; Xu et al., 2020)

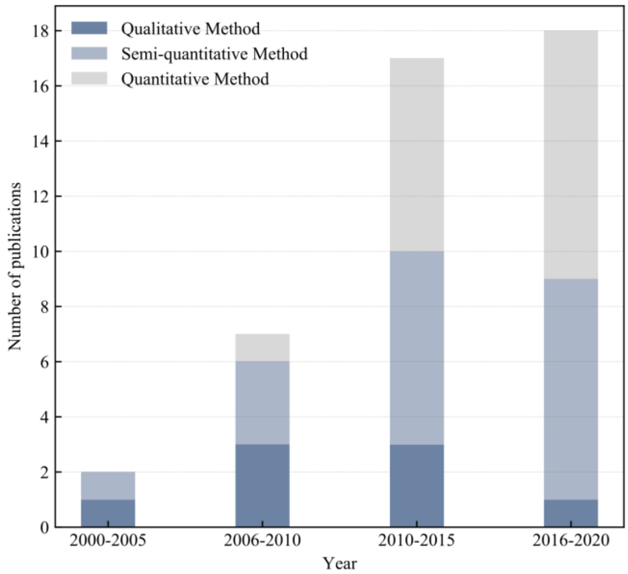


Fig. 7. Distribution of the three types of risk analysis methods over the last two decades.

3.1 Qualitative methods for risk analysis of AUV operations

Qualitative risk analysis refers to a non-numerical representation to describe the frequency and the severity of a hazardous event. The representations include flow diagrams, graphs, sources of data, and other descriptive scales (Rausand and Høyland, 2003; Khan et al., 2015). Within the domain of risk analysis of AUVs, qualitative methods emerged in the early phase, as shown in Fig. 7. A safety layer method was firstly proposed (Ortiz et al., 1999). This study analyzed the technical reliability of AUVs, emphasizing that internal fault detection in the hardware structure is an essential step to achieve safe operations. Subsequently, a failure diagnosis layer was developed for AUV mission control (Madsen et al., 2000). A tree diagram was built to represent the potential causes of mission failure.

The aforementioned qualitative research primarily used non-probabilistic models in synthesis with expert knowledge. In the early development of AUVs, qualitative methods were ideal tools to analyze operating risks owing to a lack of available data. However, few of them explicitly capture the underlying risk contributors and complex causal relationships, and thereby the overall risk level cannot be determined accurately. Hence, qualitative methods can only offer general guidelines in the AUV risk management process, and quantitative information is required to handle the inherent uncertainties of AUV operating risk.

3.2 Semi-quantitative methods for risk analysis of AUV operations

Semi-quantitative methods fall in between qualitative and quantitative methods (Khan et al., 2015). They can quantify probabilities and consequences in an approximate way and provide more detailed measurement than qualitative methods (Rausand and Høyland, 2003). Based on early research, a number of semi-quantitative approaches for risk analysis of AUVs have been proposed. The risk management process (RMP) model, the fault tree analysis (FTA) method, the event tree analysis (ETA) method, and the failure mode and effects analysis (FMEA) method have been successively applied for risk assessment of AUV operations.

A novel risk management process (RMP) model was proposed to support decision making in extreme environments (Griffiths and Trembanis, 2007), shown as Fig. 8. The proposed RMP model was the first systematic risk management approach to help an AUV team determine an acceptable risk level of deployment. It estimated the probability of AUV loss based on both expert knowledge and statistics. Applications of the RMP model have been discussed in subsequent studies (Brito et al., 2010; Griffiths and Brito, 2011; Thieme et al., 2015a).

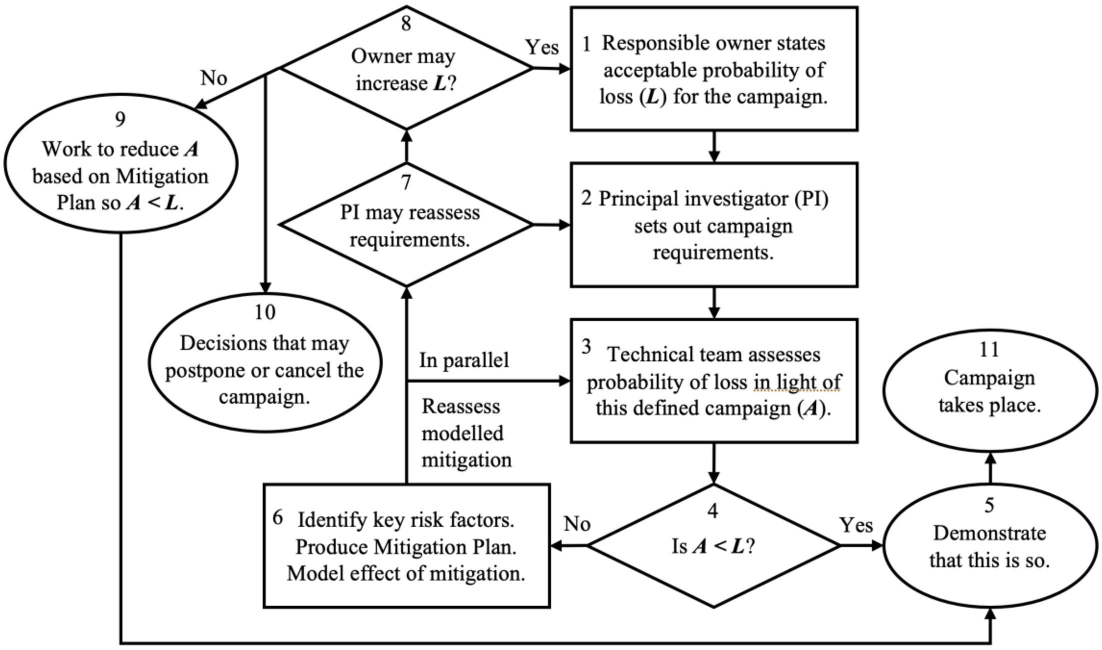


Fig. 8. The flow chart for Risk Management Process (RMP) of AUVs (Griffiths and Trembanis, 2007)

The FTA method was widely used in the technical reliability analysis of AUVs (Bian et al., 2009a, b; Xu et al., 2013). In these studies, AUV mission failure was denoted as the top event, whereas the subsystem failure or component failure were identified as root causes. During a qualitative analysis, the fault tree was built to depict the failure propagation and logical relationships between root causes and the top event. The Monte Carlo random simulation was subsequently used to assist in quantitative calculation. ETA is another method which is capable of mapping causal relationships between a hazardous event and the consequent sequence. Three consequences have been analyzed using the ETA model, including AUV mission failure, mission abort, and the loss of an AUV (Thieme et al., 2015a; Brito et al., 2018). FMEA is a recommended method for the underwater robotic industry to identify the component-level failures and their effects on the system (Veritas, 2003; Aktiengesellschaft, 2009; Harris et al., 2016). For instance, FMEA was applied to analyze different failure modes for an AUV mechanical system (Hu et al., 2013). Key components including the sealing elements and hermetic hulls were identified, which have the greatest impact on mechanical system failure.

By comparison, key conclusions can be drawn. Firstly, for the component level or the subsystem level, FMEA is quite suitable for preliminary risk analysis. Since a component or a subsystem has relatively constrained failure modes and simpler causal relationships, FMEA can be easily used to identify risky elements. In addition, fault data, such as the mean time between failures, can be determined to quantify the component failure rate. Such quantitative methods can provide a more accurate way for identifying critical components and implementing suitable safety measures. However, for the whole vehicle level, FTA and ETA can be ideal tools for systematic risk analysis. These two methods can help to better identify the underlying contributors to overall vehicle failure, the interactive relationships between AUV subsystems, and the failure propagation pathway. In order to perform a more holistic and reasonable risk analysis for AUVs, combined analysis using these methods can be considered.

To sum up, semi-quantitative methods perform well in analyzing potential failure modes, possible consequences, and necessary safety barriers in the AUV domain. However, as the basic data applied in these approaches are mainly estimated by experts or by random sampling methods, bias and uncertainties are inevitably introduced and may accumulate during the analysis process. Thus, although semi-quantitative methods provide a valuable reference in initial risk analysis, quantitative methods are further required to reduce uncertainties and enhance the analysis accuracy.

3.3 Quantitative methods for risk analysis of AUV operations

Quantitative risk analysis provides a numerical estimation for probabilities, consequences, and severities (Rausand and Høyland, 2003). A remarkable benefit of quantitative methods is that they offer a reliable reference for tackling uncertainties and informing decision making (Khan et al., 2015). More recently, extensive studies have been carried out that lay the foundation for quantitative risk analysis of the deployment of AUVs. Three typical methods are comparatively introduced in the following subsections, namely, Bayesian Belief Network, Markov chains, and the system dynamics method. Their main characteristics are summarized in Table 6.

3.3.1 Bayesian Belief Network

The Bayesian belief network (BBN) model has been widely used for risk analysis of AUV deployments. In general, BBN is a directed acyclic approach using Bayes' theorem as the key inference mechanism (Weber et al., 2012). The variables in BBN (i.e., risk factors) are represented by nodes, while the arcs links between the nodes denote the causal effect relationships. One of the key advantages of BBN is that conditional dependency degrees of nodes can be indicated by conditional probabilities (Song et al., 2016). This feature facilitates the BBN to provide more accurate risk prediction in a probabilistic way, even when information is scarce.

So far, within the domain of risk analysis of AUVs, the BBN model is mainly used for estimating the risk of AUV loss (Griffiths and Brito, 2008; Brito and Griffiths, 2016) and monitoring the mission success (Thieme et al., 2015b; Hegde et al., 2018). It was first used for estimating the risk of loss of AUVs in a sea ice environment (Griffiths and Brito, 2008). Operations under sea ice or ice shelves may involve significant risks to AUVs. Earlier methods for assessing the risk were mainly based on expert judgment. However, subjective expert judgment can hardly provide accurate risk estimation. Thus, a solution using BBN was proposed (Griffiths and Brito, 2008). The causal effects of the environments and the vehicle were captured in their study, and the expert judgment was included to provide conditional probabilities of the BBN model. By quantitative calculation, the probability of vehicle loss was obtained. An extended study also applied BBN for predicting the risk of AUV loss (Brito and Griffiths, 2016). Ice concentration, ice thickness, environmental constraints, and vehicle types were highlighted as the main contributors to AUV loss.

Another application of the BBN model for monitoring AUV mission success was proposed (Thieme et al., 2015b). The risk influencing factors (RIFs), which can cause the mission to abort, were modeled in their study. Although the BBN model was proved as an effective method to assess risks prior to executing a mission, the study lacks quantitative analysis for the relationships among RIFs. To address this problem, an extended study presented a novel BBN model to quantify the probability of mission success during the submarine operations of inspection, maintenance, and repair (IMR) (Hegde et al., 2018). Through this BBN model, the RIFs that affect the failure of IMR missions were identified and topologized, including technical, organizational, and operational factors. The established BBN model is relatively systemic and holistic, which can support the decision making of human supervisors to achieve safe IMR operations.

In comparison to the aforementioned risk analysis methods for AUVs, such as FTA, ETA, and others, the BBN model has advantages in several aspects. Firstly, it is a probabilistic method that can quantify both the relationships among RIFs by conditional probabilities and the probability of a target node, such as AUV loss and mission failure. Deriving the conditional probabilities can be a resource demanding process. Given the scarcity of historical accident data, using data driven approaches to obtain the conditional probabilities may not be applicable in the AUVs domain. The involvement of expert judgment can be an alternative solution. Thus, the basic data used to quantify the BBN model can be elicited from expert knowledge rather than empirical data. Secondly, the BBN model can be updated by incorporating new evidence, and thereby it can produce an updated mission abort probability. This characteristic is particularly suitable for dynamic undersea environments. In addition to the subsea oil and gas industry, the potential application of the BBN-based risk analysis method can be adapted to other domains, such as deep-sea mining and aquiculture, that may utilize AUVs for routine submarine operations.

3.3.2 Markov Chains

A Markov chain is a widely-used stochastic model for reliability analysis (Gagniuc, 2017). A detailed description and application of the Markov chain model have been well presented in previous research (Grimes, 1970; Alam, 1986). Here, a significant property should be emphasized: finite discrete states of a system are included in the Markov chain, and the state transition probability (STP) to the next state is only determined by the current state, rather than historical states' information. Therefore, the Markov chain is suitable for predicting the occurrence probability of a future state.

In an AUV mission, a complete deployment process from the initial predive test to final recovery comprises sequential phases, and varied risks and failure characteristics pertain to different phases. For instance, higher risks are associated with the launch and recovery phases (Griffiths et al., 2007a). Given that a Markov chain can identify system states and quantify the STP of a sequence of operations, it can be chosen as an ideal method for the risk analysis of AUV deployment.

A critical element for the application of the Markov chain is estimating the STP. Basic data have been provided from a former study, which illustrated the generic information of the AUV operation process and assigned the probability of AUV loss for 63 incidents (Griffiths and Trembanis, 2007). However, insufficient data generated in this study did not fully cover the STP of the whole deployment chain. To overcome this limitation, a systematic Markov chain approach was proposed for modeling AUV risk in different phases and quantifying risk for multiple scenarios (Brito and Griffiths, 2011; Griffiths and Brito, 2011). With the elicitation of domain experts' judgment, these studies addressed unobtainable SPT data from existing research. The developed Markov chain method consists of two steps. The first establishes a topological structure that encodes the sequential phases of a deployment life cycle. A total of 11 states are identified, as shown in Fig. 9. The state description and different risks involved in each phase of AUV deployment are summarized in Table 7. In the second stage, the STP is determined by embedding the extended Kaplan-Meier survival statistics. Hence, with the integration of the Markov chain and survival statistics, the success probability of each state and of achieving the overall mission goal can be quantified.

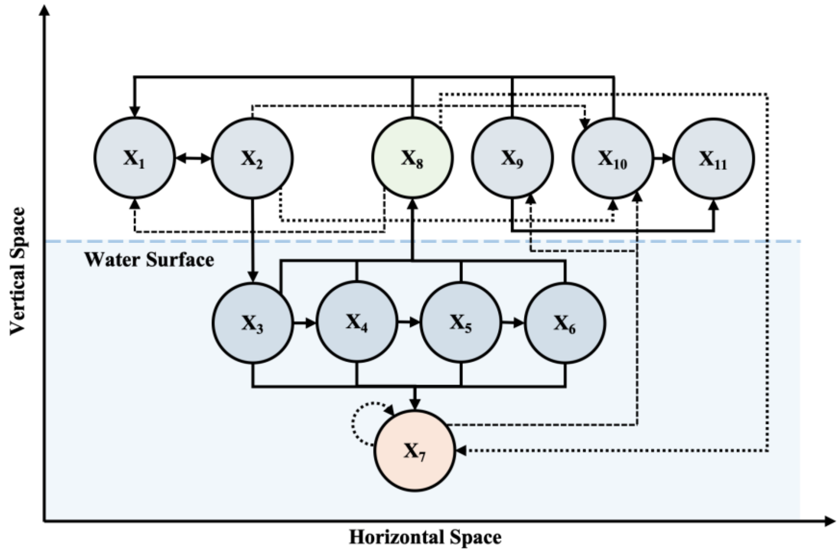


Fig. 9. Markov chain model capturing the sequential phases of the AUV deployment, adapted from (Brito and Griffiths, 2011).

Table 7. State description and risk involved in each phase of AUV deployment.

State Number	State Name	State Description	Risk Involved
X_1	Pretest state	Fault identification and rectification	-
X_2	Post-test state	Ready to launch	-
X_3	Overboard state	Ready for predive checks	Loss risk next to a deployment platform
X_4	Diving	Proceed with the mission	Uncontrolled dive, Loss risk
X_5	Holding/test Pattern phase	Test during the first dive	Loss risk
X_6	Underway state	Proceed with the mission	Loss risk
X_7	Loss	Temporary or permanent loss of the vehicle	Loss risk
X_8	Recovery	Recover the vehicle	Loss risk, collision risk
X_9	Find	Find the vehicle	-
X_{10}	Salvage	Salvage the vehicle	Loss risk
X_{11}	Scrap	Scrap the vehicle as being beyond economical repair	-

The application of the Markov chain in their study proved it is effective for the risk analysis of multiple phases of AUV deployment. Transparency is injected through its clear graphical structure, which facilitates the risk estimation of each state and the overall mission achievement. However, a simple assumption is made in this method: the AUV risk is quantified as a function of the traveled distance. As the mission formats become more complex and dynamic in unpredictable environments, especially with the interaction of multiple vehicle platforms, an extended study based on the Markov chain is required as a suitable solution to provide updating STP in future studies.

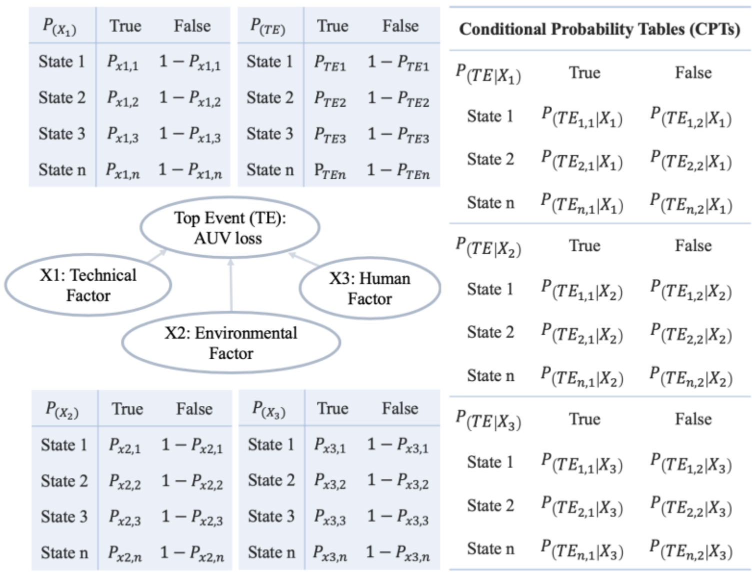
3.3.3 System Dynamics

The system dynamics (SD) method was proposed for the analysis of dynamic complex systems (Forrester, 1997). It is an objective-oriented deterministic approach to understand non-linear behavior of the system in real time by using internal feedback loops, stock and flow structures, and time delays (Sterman, 2010). The central concept of the SD method is that it uses feedback control to represent how the system structure responds to dynamic behavior (Loh et al., 2020c). Given that this method can effectively model both the dynamic nature of the risk and causal relationships among risk contributors, SD has widely served as a risk analysis method for complex systems.

For the risk analysis of the AUV system, the SD method was first used to analyze risk mitigation influenced by multiple AUV deployments (Brito and Griffiths, 2012). This attempt analyzed the risk mitigation efforts influenced by multiple AUV deployments, which focused on human resource management. Although this study lacks a structured framework and validation of the proposed method, it proves the capabilities of the SD method applied for risk analysis in the AUV domain. Furthermore, a system-based SD framework was first proposed for analyzing the risk of AUV loss (Loh et al., 2020c). Presented as a structured framework, this study mainly examined the human error incident rate in Antarctic AUV programs and produced policy recommendations. The strength of the SD method is well recognized in this study: complex causal relationships between risk factors can be modeled, and the dynamic nature of these contributors can be captured effectively by the stock and flow structures. However, solely applying the SD model to analyze risk factors has its drawbacks. Risk is often viewed as derived from uncertainties, which features the risk with a multi-dimensional, dynamic, and fuzzy nature (Haimes, 2009). However, such uncertainties cannot be explicated expressed by the deterministic SD model. This limitation has promoted the recent development of integrating the SD method with fuzzy logic (Loh et al., 2020a; Loh et al., 2020b; Xu et al., 2020). A resultant fuzzy system dynamics risk analysis (FuSDRA) method was proposed to achieve a more robust risk analysis for an AUV loss accident (Loh et al., 2020b). In the FuSDRA framework, the SD method modeled the dynamic interrelationships among risk variables from different dimensions such as human and organizational factors, technical factors, and external commercial factors. At the same time, fuzzy logic was integrated to account for stochastic uncertainties of risk variables and their interrelationships. An extended study used the FuSDRA approach for exploring the relationships between AUV crews' experience and the risk of AUV loss (Loh et al., 2020a). It was the first time that the FuSDRA method was utilized for in-depth risk analysis of human factors. In a more specific application, the FuSDRA method was applied to analyze how the government support and technological obsolescence could influence AUV loss (Xu et al., 2020).

In conclusion, the hybrid FuSDRA approach leverages the strength while overcoming the constraints of both the SD method and fuzzy logic theory. The application of this method can facilitate risk mitigation policies provided by AUV decision makers, and these risk control recommendations are expected to be more reliable and effective in an actual deployment mission. Furthermore, the FuSDRA method can serve as a risk management method for AUV programs. In an academic aspect, it further explores the non-probabilistic concept of quantitative risk analysis. This attempt is particularly challenging for solving on-site problems when AUV performance data are not always accessible. Despite the advantages of the FuSDRA method for risk analysis of AUVs, its limitations are also identified. The major limitation is that this method heavily depends on expert judgment elicitation. Due to the unavailability of AUV performance data, the risk variables and their fuzzy rules basically lie in domain expert judgments. Different assumptions or even conflicting perceptions can be derived from experts with varied levels of experience. As a result, biases are inevitably introduced when developing the FuSDRA framework. Therefore, further improvement can consider assignment of weights and the confidence level of domain experts to reduce the subjective biases.

Table 6. Characteristics of the three risk analysis methods.

<table>
<tr><th>Risk Analysis Method</th><th>Basic Model</th><th>Advantages</th><th>Limitations</th></tr>
<tr><td>Bayesian Belief Network</td><td>
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- BBN provides quantitative and intuitive estimates for AUV decision-makers of the probability of different risk profiles before a mission, which is particularly valuable in the early utilization phase of an AUV when historical fault data is limited.
- Risk factors and their interactive relationships can be systematically identified and topologically represented by the BBN model.
- Critical risk factors can be determined by comparing the differences between post probabilities and prior probabilities.
- The BBN model can be updated in real time when new evidence is involved, which is beneficial for AUV missions in dynamic subsea environments.

</td><td>

- The process of risk nodes identification, states definition, and allocation of conditional probabilities may refer to expert judgment elicitation, which induces uncertainties and biases in the BBN model.
- With the increase of the number of risk nodes and the complexity of their interrelationships, it is relatively difficult to calculate the conditional probabilities and apply the BBN model.

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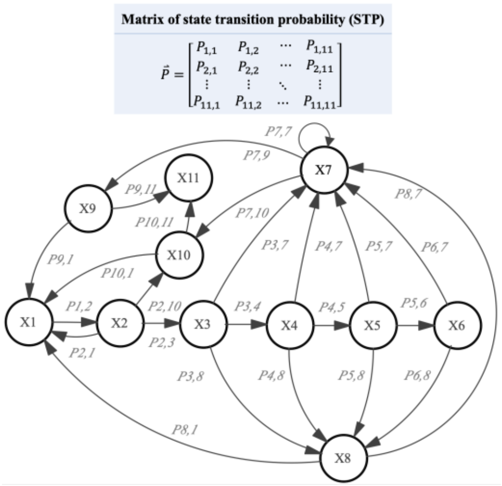
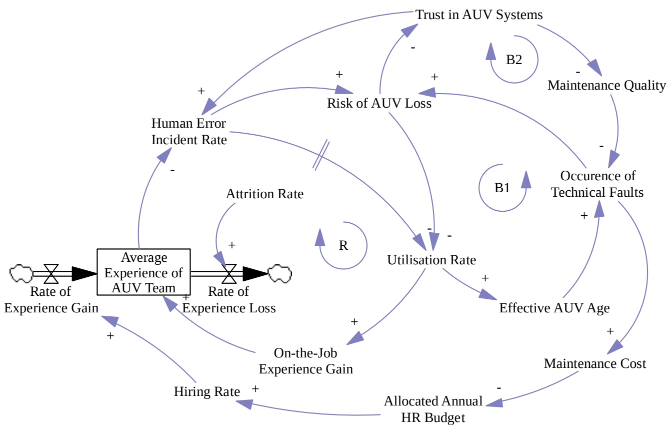
Markov Chains		• The Markov chain is well-suited to identify distinct states and state transitions involving risks. Thereby it can model the complete sequence of an AUV mission from prelaunch to recovery and facilitate risk identification of each mission phase. • The Markov chain is a valuable tool for predicting the risk of mission abort. It allows for quantifying the success probability of each state by using STP, and it iteratively calculates the success probability of the final mission goal.	• The Markov chain requires estimation for STP, which are usually derived from expert knowledge when historical data are unobtainable. This process may lead to judgmental biases. • The Markov chain is limited to represent and explain the underlying risk contributors and their causal relationships.
System Dynamics		• Complex causal relationships between risk factors of different dimensions can be captured effectively in the causal loop diagram. • Dynamic behaviors of risk factors can be represented by stock and flow structures. This characteristic is particularly useful for time dependent AUV missions. • Without complex probabilistic computations, the SD model is relatively easy to understand and apply.	• The complexity of the SD model would rapidly increase with the number of risk variables. Defining each risk variable and its correlation equations can be challenging and time-consuming. • The deterministic nature of the SD model cannot cope well with the uncertainties in interrelationships of risk factors, especially for soft factors like human factors, which are difficult to quantify explicitly using equations.

4. Future challenges for risk analysis of AUV operations

Based on the above analysis of past progress, section 4 identifies current research gaps and discusses future challenges in the domain of AUV risk analysis.

4.1 Dynamic risk analysis for AUV operations

In general, the dynamic nature of AUV deployment risk results from two factors. The first is the complexity of the AUV itself. Many components and subsystems contribute to the functioning of the AUV system. The interaction between hardware and software leads to both physical and functional dynamics. Secondly, AUVs usually operate in highly dynamic marine environments. Unsteady working conditions result in the dynamic nature that evolves with time and space. Thus, due to the dynamic nature, real-time decision making in uncertain underwater environments is quite challenging.

For now, the majority of risk analysis models applied to AUV deployment are traditional methods that have a static structure, which cannot capture dynamic uncertainties existing in the complex AUV system and harsh environments. Therefore, dynamic risk analysis (DRA) methods are required. DRA is defined as a method which is capable of updating risk estimation dynamically. The key difference between traditional risk analysis methods and a DRA method is that DRA can monitor and assess abnormal conditions and revise the overall risk level when new information is incorporated. In the AUV domain, tailored DRA methods are demanded to provide a dynamically adaptable way to monitor and measure the risk estimation of AUV deployment. Effective and timely risk analysis is vital to predict an abnormal situation and prevent accidents. Adopting DRA methods will help decision making based on the real-time situation, inform stakeholders to take early actions before accidents occur, and enable safer performances of AUVs operating in extreme environments.

4.2 Risk analysis for AUVs with scarce historical data

Historical data reveal the fault and incident information of AUV performances. This is the fundamental information required in many traditional risk analysis models, including FTA, ETA, BBN, and so on. Historical data is essential for accurate risk estimation. However, in the early phase of the utilization of an AUV platform, accidental data tend to be limited or scarce. In this case, the data source for risk analysis models is hard to obtain, and thus, it is challenging to conduct accurate risk estimation.

When data is insufficient for accurate probabilistic quantification, combining domain expert knowledge can be compensatory. By incorporating expert judgments into the risk analysis process, the absence of data can be substituted by qualitative information. However, merely relying on experts may lead to judgmental uncertainties, which indicates a need for more advanced methods to address missing data problems in future studies. Such advanced methods can compensate for missing data in a quantitative way and additionally use the data to predict in-situ risk estimation. Machine learning techniques have great potential to tackle data limitation problems. A number of studies have used machine learning algorithms to improve the quantification accuracy under scarce data conditions (Ramoni and Sebastiani, 2001; Elidan et al., 2002; Elidan and Friedman, 2012; You et al., 2019), and provide valuable references to the AUV domain. Hence, machine learning based methods are effective tools for future research to reduce the dependence on historical data and expert judgments, and improve the accuracy and efficiency of risk estimation with incomplete data.

4.3 Intelligent risk analysis for AUV operations

Intelligent behaviors of an autonomous system are defined as onboard capabilities of decision-making, mission planning and re-planning, and fault tolerance (Seto, 2012). With the development of AUV technologies, risk analysis of AUV operations is broadening to an intelligent scope (Bremnes et al., 2019). Intelligent risk analysis in the AUV domain refers to performing risk analysis and decision making by the vehicle system itself instead of human operators. More specifically, intelligent risk analysis enables the vehicle to process real-time data, assess in-situ risk level, adapt path planning and motion control strategies according to current risk scenarios, and assist the vehicle to accomplish a mission autonomously without much human intervention.

Most of the classic risk analysis methods applied in the AUV domain are based on the offline assessment before a mission. These methods aim to assist operators to estimate the current risk level, take necessary risk mitigation measures, and adapt their mission plans accordingly. However, traditional offline risk analysis relying on humans tends to be time-consuming. Time delays caused by manual analysis processes will result in real-time risk scenarios that cannot be precisely identified. Delayed risk identification will successively compromise the accuracy of current risk estimation and reduce the effectiveness of subsequent decision making. This leads to the consideration of changing the way of risk analysis from human offline prediction to autonomous online risk analysis.

Intelligent risk analysis can be a game-changer in future trends of risk analysis for autonomous vehicular systems. A potential solution is combining classic risk analysis models with machine learning techniques, and subsequently incorporating them into the online decision system. Currently, a number of studies have adopted machine learning methods to aid onboard risk analysis in the marine robotics domain (Liu et al., 2012; Zhang et al., 2015; Hollinger et al., 2016; Xiang et al., 2017). The major advantage of machine learning algorithms is their self-learning capabilities to explore all possible interactions between non-linear input and output risk variables (Tu, 1996; Bevilacqua et al., 2010; Hegde and Rokseth, 2020). High computational speed enables them to achieve real-time risk prediction with much higher efficiency than human operators. In addition, a wide variety of data are continuously generated from sensor platforms. Machine learning techniques can process various forms of these data, including numerical data, textual data, and image data. The combination of data information is used to assess in-situ environmental and operational conditions, and thus achieve more systematic and accurate risk estimation. Therefore, the online decision system can take reasonable actions based on the current risk state. To sum up, in order to improve the autonomy level of AUVs and increase the effectiveness as well as the efficiency of risk analysis, intelligent risk analysis is expected to be developed as an integral part of an AUV system.

4.4 Risk analysis for multi-AUV collaboration

As the technology of AUVs gradually matures, multi-AUV mission formats are rapidly emerging (Harris et al., 2016). Multi-AUV missions refer to the cooperative work of multiple AUVs to achieve a mission goal. As the mission format becomes more synergic, the multi-AUV system can cruise larger areas and complete more difficult tasks than a single vehicle. At the same time, as the multi-vehicle operations are more interactive and dynamic, operational risks inevitably become more complex and thus require effective analysis. However, most of the current risk analysis research has concentrated on traditional single-vehicle missions and cannot represent the interactive risk associated with multiple platforms. Therefore, novel methods are required in future research to facilitate the risk analysis for multi-AUV collaboration.

When conducting risk analysis for a multi-AUV scenario, the interactive impact among multiple vehicles is a key consideration. During the cooperation between two vehicles, reliable communication is needed for data updates and data transmission. This process requires consideration of the constraints of space and time for both vehicles within dynamic underwater environments whilst preventing collisions. On the other hand, the interaction between vehicles can influence the risk among vehicles. For example, if failures occur in the navigation system and the vehicle takes incorrect headings, the likelihood of colliding with nearby vehicles can be increased. Therefore, future studies of risk analysis for multi-AUV collaboration should ensure the cooperative efficiency whist improve the safety performance of all platforms.

5. Summary and conclusion

The main objective of this study is to provide a systematic review of past progress of risk analysis research for AUV operations. This review answers key questions denoted in Section 1, including fundamental concepts and implemented methods in the domain of risk analysis for AUVs, and it highlights future research trends to bridge existing gaps. The scope of this article is restricted to topics directly related to the research questions. Based on the aim and scope of this study, a total of forty-four articles with significant relevance to AUV related risk analysis were retrieved. The underlying risk factors identified from selected literature are summarized into three categories: technical factors, environmental factors, and human factors. A comparative analysis was undertaken to provide a clear picture of the evolution process, advantages, and limitations of adopted risk analysis methods from qualitative, semi-quantitative, and quantitative aspects. Current research gaps and future challenges in this domain were briefly outlined.

In light of the review and analysis, three key conclusions can be drawn. Firstly, systematic identification of risk factors and their causal relationships are vital for further risk analysis. Most of the early research focused on technical factors of AUVs, relying on historical performance data. Whereas in current trends, environmental factors, human factors, and their interactive impacts, are increasingly receiving attention. Subsequently, it is evident that quantitative methods have been rapidly implemented in recent years to enhance the accuracy and handle the uncertainties of risk analysis of AUVs. However, former studies still heavily rely on expert knowledge, which may introduce judgmental bias. Lastly, future challenges for risk analysis for AUVs may include addressing dynamic risk analysis, scarce historical data, intelligent risk analysis, and multi-vehicle risk analysis.

Appendix

Table 8. Classification of literature with respect to the risk analysis of AUVs.

No.	Literature	Risk Factor Identification			Risk Analysis Method		Mission Type	Mission area	Consequence Type
		Technical Factor	Environmental Factor	Human Factor					
1	(Ortiz et al., 1999)	✓			Safety layers analysis	Qualitative	General mission	General area	AUV abnormal working
2	(Madsen et al., 2000)	✓			Tree diagram	Qualitative	Deep water and under ice mission	General area	Mission abort
3	(Griffiths et al., 2003)	✓			Kaplan-Meier survival model	Semi-quantitative	Under sea ice mission	The Antarctic	AUV loss
4	(Griffiths and Trembanis, 2007)	✓			RMP	Semi-quantitative	Under sea ice and ice shelf mission	Polar regions	AUV loss
5	(Griffiths and Brito, 2008)		✓		BBN	Quantitative	Under sea ice mission	Polar regions	AUV loss
6	(Bian et al., 2009a)	✓			Fuzzy FTA	Semi-quantitative	General mission	General area	AUV abnormal working
7	(Bian et al., 2009b)	✓			FTA, Monte-Carlo simulation	Semi-quantitative	General mission	General area	AUV abnormal working
8	(Brito et al., 2010)		✓		RMP, Kaplan-Meier survival model	Semi-quantitative	Under sea ice and ice shelf mission	The Antarctic	AUV loss

9	(Meng and Qingyu, 2010)	✓			Safety measures analysis	Qualitative	General mission	Lake area	Battery failure, leakage, fishing net wrapped
10	(Kaminski et al., 2010)		✓		Fault Response Table	Qualitative	under ice bathymetric surveys	The Arctic	AUV loss
11	(Brito and Griffiths, 2011)	✓	✓		Markov chain	Quantitative	General mission	General area	AUV loss
12	(Griffiths and Brito, 2011)	✓	✓		RMP, Markov chain	Quantitative	Under sea ice mission	Polar regions	AUV loss
13	(Ho et al., 2011)			✓	/	/	General mission	General area	Mission abort
14	(Brito et al., 2012)	✓			BBN	Quantitative	Under sea ice mission	The Arctic	Operational risk
15	(Brito and Griffiths, 2012)	✓			SD	Quantitative	Multi-AUVs mission	General area	AUV loss
16	(Hu et al., 2013)	✓			FMECA, FTA	Semi-quantitative	General mission	General area	AUV loss, mission abort
17	(Xu et al., 2013)	✓			FTA, Monte Carlo simulation	Semi-quantitative	Deep-sea minerals exploration	Deep-sea hydrothermal area	Mission abort
18	(Pereira et al., 2013)		✓		Markov decision process	Quantitative	Path planning	General area	AUV collision
19	(Merckelbach, 2013)		✓		Monte Carlo simulation	Semi-quantitative	General mission	General area	Glider loss, collision with ships
20	(Aslansefat et al., 2014)	✓			FTA	Semi-quantitative	General mission	General area	AUV abnormal working
21	(Brito et al., 2014b)	✓			Probability tree model	Quantitative	General mission	General area	Loss of communication

22	(Brito et al., 2014a)	✓			Monte Carlo simulation, Kaplan-Meier survival model	Semi-quantitative	Shallow water and deep-water glider mission	Shallow water, deep water	AUV collision
23	(Zhang et al., 2015)	✓			Grey relation analysis	Qualitative	General mission	General area	Thruster fault
24	(Thieme et al., 2015b)	✓	✓	✓	BBN	Quantitative	General mission	General area	Mission abort
25	(Thieme et al., 2015a)	✓	✓	✓	Risk management framework, human reliability analysis, FTA, ETA	Semi-quantitative	Map the seafloor	Coastal area	AUV loss, mission abort
26	(Brito and Griffiths, 2016)		✓		BBN, Kaplan-Meier survival model	Quantitative	Under sea ice mission	the Antarctic	AUV loss
27	(Zeng et al., 2016)		✓		Particle swarm optimization algorithm, Monte Carlo simulation	Quantitative	Path planning	environments with ocean currents	AUV collision
28	(Hegde et al., 2016)	✓	✓		Risk indicator model	Semi-quantitative	Subsea IMR operation, path planning	General area	AUV collision
29	(Lefebvre et al., 2016)	✓			HPA-Star algorithm	Quantitative	Subsea IMR operation, path planning	General area	AUV collision
30	(Harris et al., 2016)	✓			FMEA, FTA, Markov Decision Process	Semi-quantitative	Multi-vehicle mission	General area	AUV loss

31	(Brito, 2016)	✓			FTA	Semi-quantitative	General mission	General area	Glider mission abort
32	(Yu et al., 2017)	✓	✓		Bow-tie	Qualitative	IMR operation of offshore oil and gas platform	General area	AUV collision
33	(Xiang et al., 2017)	✓			FTA, Mamdani fuzzy neural network	Semi-quantitative	General mission	General area	Failure of onboard system
34	(Hegde et al., 2018)	✓	✓	✓	BBN	Quantitative	Subsea IMR operation	Åsgard field, Norway	Mission abort
35	(Brito et al., 2018)			✓	ETA	Semi-quantitative	Adaptive mission planning (AMP)	General area	Failure of AMP
36	(Brito and Griffiths, 2018)	✓			BBN	Quantitative	General mission	General area	Mission abort, AUV loss
37	(Brito and Chang, 2018)	✓			FTA	Semi-quantitative	General mission	General area	AUV loss
38	(Hegde et al., 2019)	✓	✓		Safety envelop, Octree method	Semi-quantitative	Subsea IMR operation, path planning	General area	AUV collision
39	(Loh et al., 2019)	✓	✓	✓	Fuzzy set theory	Semi-quantitative	Under sea ice mission	the Antarctic	AUV loss
40	(Bremnes et al., 2019)	✓	✓		BBN	Quantitative	Under ice altitude control	The Arctic	AUV loss
41	(Loh et al., 2020a)	✓		✓	FuSDRA	Quantitative	Under sea ice mission	the Antarctic	AUV loss
42	(Loh et al., 2020b)	✓	✓	✓	FuSDRA	Quantitative	Under sea ice mission	the Antarctic	AUV loss
43	(Loh et al., 2020c)			✓	SD	Quantitative	Under sea ice mission	the Antarctic	AUV loss
44	(Xu et al., 2020)	✓		✓	FuSDRA	Quantitative	Under sea ice mission	the Antarctic	AUV loss

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Nomenclature

Acronym	Definition
ABE	Autonomous Benthic Explorer
AUVs	Autonomous underwater vehicles
BBN	Bayesian belief network
BT	Bow-tie
DRA	Dynamic risk analysis
ETA	Event tree analysis
FMEA	Failure mode and effects analysis
FTA	Fault tree analysis
FuSDRA	Fuzzy system dynamics risk analysis
IMR	Inspection, maintenance, and repair
RIFs	Risk influencing factors
RMP	Risk management process
SD	System dynamics
STP	State transition probability

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