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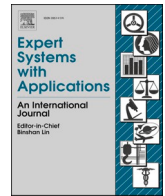
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A decision-making framework for selecting an MBSE language—A case study to ship pilotage

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ABSTRACT

The increasing system complexity due to technological advances in recent decades requires the implementation of Model-Based System Engineering (MBSE) languages. While MBSE languages can support in creating detailed and precise system descriptions, requirements, functions, and component interactions, the development of several modelling languages has formed a challenge for system engineers to select a suitable modelling language for complex operations. Since the implementation of MBSE modelling languages is extensive and requires high resources, system engineers need to select the most suitable one for their project. Furthermore, the prepared system models are utilized by different end-users such as system engineers, operators, and marketing professionals. As a result, it is necessary to integrate the perception of end-users in the modelling language selection process. Hence, a decision-making support framework needs to be developed, which will incorporate the opinions of end-users in the selection process. Correspondingly, this study proposes a Multi-Criteria Decision-Making framework aimed to select the most appropriate and practical modelling language. The framework integrates the end-user's perception in the selection process using the Technology Acceptance Model and reckons the MBSE language features as comparison criteria. To analyze the data collected from the end-users, integration of Multinomial Process Tree modelling and Bayesian inference is developed. The applicability of the proposed model was tested in a ship pilotage operation case study. The results show that the framework can support system engineers during the initial selection process of the MBSE modelling language.

1. Introduction

1.1. Background

Due to technological advances, the system's complexity is growing faster than it can be effectively managed (Benbya & McKelvey, 2006; Sames, 2019). In the marine domain, numerous stakeholders are currently exploring the development of autonomous ship concepts (Kongsberg, 2020). Autonomous ship systems are expected to be relatively more complex than traditional ships as the increased functionalities of these systems are integrated with more advanced and embedded software (Levander, 2017). To understand and manage these complex systems, it is necessary to have clear descriptions or specifications of system components, interactions, functions, and requirements, (Hollnagel, 2012; Leveson, 2011). However, the traditional document-centric

approaches for system descriptions have several limitations such as system updates integration, miscommunication, ambiguity, inconsistent terminology, and disrupted system information representation (Kalawsky et al., 2013; NASA, 2018). As a potential solution, MBSE methods have become increasingly popular among system engineers in recent decades (Grobshtein et al., 2007; Kalawsky et al., 2013; NASA, 2018).

According to the International Council on Systems Engineering (INCOSE, 2007) "MBSE is the formalized application of modelling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases". MBSE aims to create, analyse, manage, and communicate the system description through simple, clear, and concise computer-interpretable models. These models allow improved communication with stakeholders through enhanced system description models and information

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exchange. Thus, several researchers have demonstrated the capabilities of system modelling using MBSE by applying these methods in complex system development across multiple domains. In the marine domain, MBSE has been applied to develop the system architectures in naval ship design (Tepper, 2010), advanced ship machinery modelling and simulation (Papanikolaou, 2019), and system description of autonomous boats (Solberg, 2018). Similarly, MBSE has been used in conceptual design in other domains such as satellite development (Anyanahun & Edmonson, 2018; Kaslow et al., 2017), robotics (Vazquez-Santacruz et al., 2019), and Aeronautics (Gough & Phojanamongkolkij, 2018). Furthermore, MBSE has been used in different system analyses such as safety analysis (Baklouti et al., 2019), security analysis (Best et al., 2007), system simulation (Rahman & Mizukawa, 2013; Rousseau et al., 2014), and trade-off analysis (Spyropoulos & Baras, 2013).

Although several benefits of MBSE have been discussed by different researchers (Delligatti, 2014; Estefan, 2008; Friedenthal et al., 2015), the selection of modelling language for MBSE is still a challenge for organizations (Amorim et al., 2019; Reichwein & Paredis, 2011). To date, several modelling languages such as Flow Thing Modelling (FTM), Capella, Modelling and Analysis of Real-time and Embedded systems (MARTE), Architectural Analysis and Design Language (AADL), System Modelling Language (SysML) and Object Process Methodology (OPM) are available. As each of these methods has its own features including semantics, notation and graphical representation (Grobshtein et al., 2007), the suitability of application may differ (Hallqvist & Larsson, 2016; Kordon et al., 2013). Furthermore, the application of these methods requires high upfront resource investment (Chami & Bruel, 2018; Hallqvist & Larsson, 2016). Thus, organizations and system engineers must invest additional efforts in the language selection process at the beginning of the system lifecycle (Amorim et al., 2019; Hallqvist & Larsson, 2016). For assisting the selection process, only a few comparison studies exist, which compare the features of different modelling languages. Nevertheless, the suitability of given applications is mainly dependent on not only their features but also the perceived benefits and usability by the end-users (Friedenthal et al., 2015; Reichwein & Paredis, 2011). The literature review shows a lack of Multi-Criteria Decision Making (MCDM) frameworks that can assist system engineers to select a suitable modelling language. As multiple criteria affect the suitability of MBSE language, this paper presents the MCDM framework, which aims to support the system engineers in the MBSE language selection process. To this end and to specify the criteria for comparing the modelling languages, the features of MBSE modelling language identified through the literature of this research area are taken into account. The main objective is to fill the current gaps by integrating the views and beliefs of end-users in the modelling language selection process. For covering this gap, the Technology Acceptance Model (TAM), a popular method to analyse and predict the acceptance of information systems by the end-users, was utilized to estimate the perceived usefulness and ease of use for each MBSE language. To analyse the contribution of different cognitive processes of end-users to the collected data, a Multinomial Process Tree (MPT) model was developed, which is a simple statistical model effective for measuring the latent cognitive capacities (Batchelder & Riefer, 1999). The end-user's knowledge together with the MPT modelling might present a source of uncertainty. Therefore, Bayesian inference is applied to the MPT model, which is an effective method to estimate the uncertainty about how reasonable that a model, parameter or hypothesis is based on all available evidence. The developed MCDM framework based on TAM, MPT, Bayesian inference was applied to a ship pilotage operation as a case study. The case study aims to select a suitable modelling language for creating system descriptions of ship pilotage operation and to demonstrate the proposed framework. Based on the case study results, the discussions, conclusions and future directions are presented in this manuscript.

1.2. Review of MCDM frameworks and data analysis techniques for MBSE language selection

Despite the rapid increase in application, MBSE is still a relatively new discipline in system engineering (Reichwein & Paredis, 2011). Moreover, there are only a few comparison studies and one MCDM framework related to MBSE. A framework proposed by Weillkiens et al. (2016), aimed to compare and evaluate different MBSE methodologies for practitioners. Although the study includes three criteria for MBSE languages, it is more focused on the selection of MBSE methods and tools. Furthermore, the framework doesn't include any data analysis and decision-making techniques. Through the demonstration with a case study, the authors have mentioned that the framework addresses the problem for practitioners to identify the most suited MBSE methodology. However, it was noted that the results were expected to be interpreted differently by various user groups. In another study, Estefan (2008) surveyed some MBSE modelling languages, which aimed to introduce and familiarize the system engineers with different leading modelling languages. Moreover, several comparison studies of different modelling languages are available such as OPM vs SysML (Basnet et al., 2019; Grobshtein et al., 2007), AADL vs MARTE (André et al., 2008), AADL vs Event-B (Ponsard & Landtsheer, 2010), and SysML vs Flowthing Modelling (Al-Fedaghi, 2014). However, most of these studies were concluded without a clear selection among the compared methods and specified that the selection highly depends on the type of system, the purpose of application and the end-users. Thus, an MCDM framework that allows system engineers to evaluate different modelling languages by integrating the end-users in the selection process based on their desired MBSE features is still prominent to be touched upon.

1.2.1. Technology acceptance model (TAM) in MCDM frameworks

TAM, developed by Davis (1985), is one of the most popular models in analysing and predicting the acceptance of information systems by the end-users (Chuttur, 2009). The application of the TAM model in the understanding of end-users acceptance process will result in new insights that improve the design and implementation of information systems (Davis, 1985). Furthermore, it allows system engineers to evaluate the new systems or technologies before their implementation (Davis, 1985). This model argues that the actual implementation of a system is positively affected by the user's attitude toward using the system. The user's attitude toward using a system is then directly affected by the user's perceived usefulness and ease of use. Davis (1985) defines perceived usefulness as "the degree to which an individual believes that using a particular system would enhance his or her job performance" and ease of use as "the degree to which an individual believes that using a particular system would be free of physical and mental effort". Furthermore, the model argues that the user's perceived usefulness and ease of use are affected by the external variables related to the system or technology such as system characteristics and user characteristics.

TAM model has been applied in several studies such as comparing several structural equation modelling approaches (Dow et al., 2008) and evaluating different hazard analysis methods (Sulaman et al., 2019). Although TAM is widely used to evaluate the acceptance of modern technologies for replacing traditional technologies, only a few studies have utilized TAM to compare different modern technologies and methods. While the above-mentioned studies have demonstrated the usability of TAM for the integration of end-users perception, the application of TAM as a part of the MCDM framework for MBSE language selection is still lacking.

1.2.2. Data analysis techniques in MCDM frameworks

There are several data analysis and decision-making techniques that have been used under MCDM frameworks, but for a different purpose than MBSE language selection. For example, Esangbedo et al. (2021) has implemented a combination of Grey-Point-Allocation Full-consistency (Grey-PA-FUCOM) and grey-regime method for evaluating different

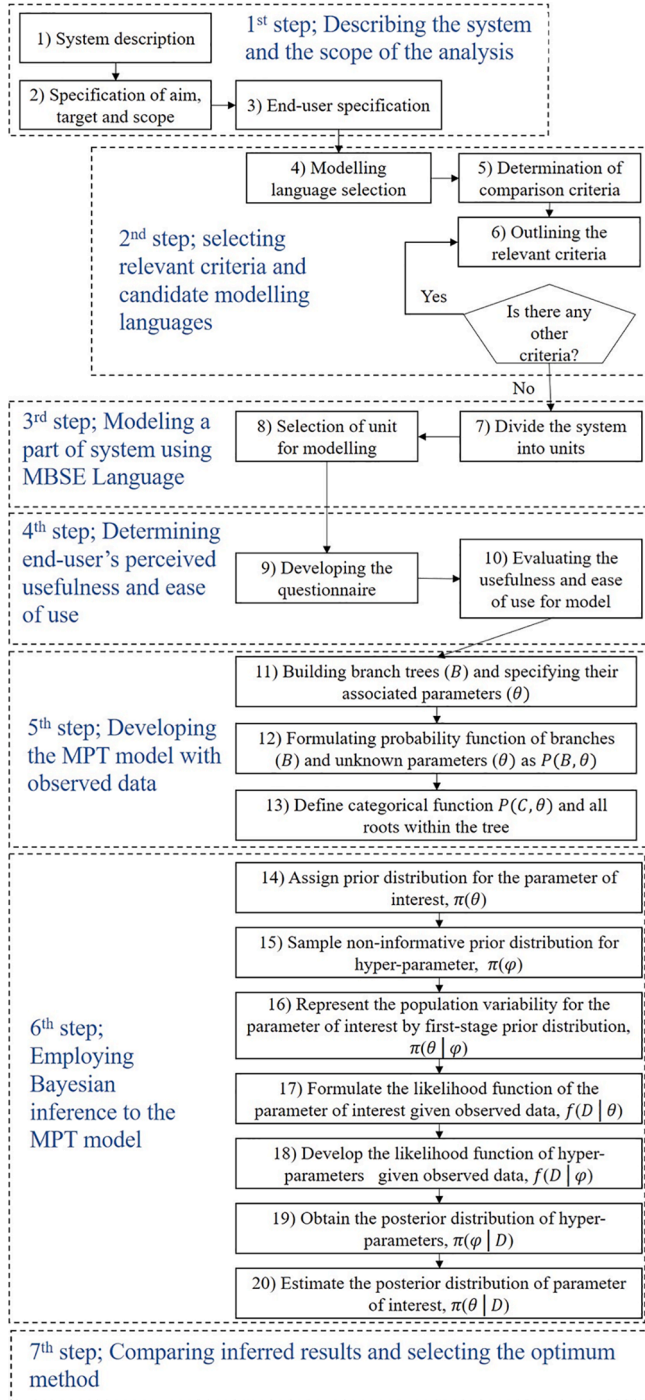


Fig. 1. The steps of the framework for the selection of modelling language.

human resource information systems. In another study, Karam et al. (2020) has employed the fuzzy approach for recruiting employee candidates by integrating systems thinking skills in an MCDM framework. Other commonly used data analysis methods have been also identified, such as the Weighted Sum Model (WSM), Weighted Product Model (WPM) and Analytical Hierarchical Process (AHP) (Mastrocinque et al., 2020). In this study, a combination of MPT and Bayesian inference is proposed for data analysis and decision-making regarding the selection of MBSE modelling language. The benefits of using MPT and Bayesian inference are highlighted in the next sections.

1.2.2.1. Multinomial process tree modelling. MPT models are described

as “simple, substantively motivated statistical models that can be used to measure underlying or latent cognitive capacities” (Batchelder & Riefer, 1999). The MPT models are exclusively developed for categorical data, where each observed data can be categorized in only one of the finite set of categories (Batchelder & Riefer, 1999). Compared with other psychometric models such as paired-comparison scaling, signal detection models etc., MPT models are statistically tractable, which makes them a better alternative for data analysis (Batchelder & Riefer, 1999). MPT models have been used for several purposes such as source monitoring (Batchelder & Riefer, 1990), pair-clustering (Batchelder & Riefer, 1986; Michalkiewicz et al., 2020), and understanding memory impairment (Lee et al., 2020). Abaei et al. (2021) has provided an MPT model for assessing the reliability of machinery in autonomous ships. The authors have developed a multinomial process tree model that simulates the behaviour of the system and then the Bayesian model was used to predict the unknown parameters and estimate the posterior probability distribution. The authors suggested that the presented method can support the decision making of autonomous ship systems and asset integrity assessment.

The above-mentioned studies have successfully demonstrated the importance of MPT models to measure and study the cognitive capacities of humans. As one of the aims of the MCDM framework proposed in this paper is to integrate the end-user's opinions on MBSE language selection, the MPT models should be used for analyzing the effect of the cognitive process on the observed data. As observed in the above-reviewed literature, the uncertainties in MPT should be studied using inference techniques such as Hierarchical Bayesian inference.

1.2.2.2. Hierarchical Bayesian inference. Hierarchical Bayesian inference is described as the process of obtaining a conclusion on the uncertainty about an unknown entity based on evidence and an aleatory model using the Bayes theorem. For an unknown parameter of interest θ , Bayes' rule combines the information from the observed data (D) with the likelihood function $f(D | \theta)$ and a prior distribution $\pi_0(\theta)$ to obtain the posterior distribution $\pi_1(\theta | D)$, which is calculated as (Bahoo-Toroodi et al., 2019):

$$\pi_1(\theta | D) = \frac{f(D | \theta) \pi_0(\theta)}{\int_{\theta} f(D | \theta) \pi_0(\theta) d\theta} \quad (1)$$

Observed data, manipulated information, and gathered knowledge are three milestones of making an inference in a theoretical model (Bahoo-Toroodi et al., 2019). The posterior distribution is achieved by updating the prior distribution with observed data. Thus, by analyzing the data, the information obtained using the Bayes theorem can be used for making inferences. As stated by Kelly and Smith (2009), the prior distribution for the parameter of interest can be expressed through a hierarchical structure as follow:

$$\pi_0(\theta) = \int_{\phi} \pi_1(\theta | \phi) \pi_2(\phi) d\phi \quad (2)$$

where $\pi_1(\theta | \phi)$ denotes the first-stage prior as the population variability in θ , ϕ is a vector of hyper-parameters. $\pi_2(\phi)$ denotes the hyper-prior distribution that aims to consider the uncertainty of ϕ (Leoni et al., 2021).

Herzig (2015) has proposed a Bayesian learning approach to identify inconsistency in model-based systems engineering. The developed approach provided probabilistic reasoning about the existence of inconsistencies and overlaps between different MBSE models. The author developed a Bayesian network to make the explicit independence of variables and then used Bayesian theory to update a prior belief of model inconsistency using evidence extracted by pattern matching.

In this study, the expert judgement used to estimate the perceived usefulness and ease of use might consist of epistemic uncertainty. In addition, representing the features through the MPT model might consist of model uncertainty. Thus, Bayesian inference should be

Table 1

The criteria related to the usefulness of MBSE language and their description (Fernandez & Hernandez, 2019; Friedenthal et al., 2015; Weilkiens et al., 2016).

Criteria related to the usefulness of MBSE language	Description of the criteria
Structural modelling	Presenting the system composition such as components list, hierarchy, and internal structure
Behavioural modelling	Presenting the system behaviour such as components functions, change of states, information exchange, command exchange and other interactions
Requirements analysis	Generating, verifying and validating the system requirements throughout its development and operational phase.
Engineering analysis	Analysing physical and performance properties of a system such as an efficiency analysis, power analysis, trade-off analysis and cost-benefit analysis
Simulation	Simulating or visualizing the system behaviour
Traceability	Linking different types of system models for easier navigability and access of the related information (defining the sources, targets and relationships)
Resources requirement	Resources required for modelling such as human, time and financial resources
International standard	Requirement related to internationally recognized certification such as ISO for ensuring low ambiguity and quality of the method
Communication	Exchange of information between stakeholders

Table 2

The criteria related to the ease of use of MBSE language and their description (Chami & Bruel, 2018; Friedenthal et al., 2015; Weilkiens et al., 2016).

Criteria related to the ease of use of MBSE language	Description of the criteria
Modelling complexity	Difficulty in creating or interpreting the system models
System complexity management	Features to manage the system complexity such as system decomposition and abstraction levels
Training support	Availability of training (online training, workshops etc) for end-users

Table 3

5-point Likert scale for rating the comparison criteria.

Rating	Corresponding detail
1	Strongly disagree
2	Disagree
3	Undecided
4	Agree
5	Strongly Agree

employed within this MCDM framework to estimate the uncertainty associated with both the expert knowledge and the MPT model and make decisions accordingly.

2. Methodology

Fig. 1 presents the seven steps of the proposed MCDM framework. The process starts with describing the system and the scope of the analysis. Based on the scope, the criteria for the comparison of modelling languages are selected by the end-users. Next, the MBSE modelling languages are applied to model a part/sub-system with inputs from end-users. The end-user's perceived usefulness and ease of use are then determined for each language by assessing the developed models. To this end, the questionnaires provided in Appendix 1 will be employed to generate the data about end-users perceived usefulness and ease of use. Next, is to establish a categorical modelling tool to analyse the data. For this purpose, the MPT model is developed and updated with the data

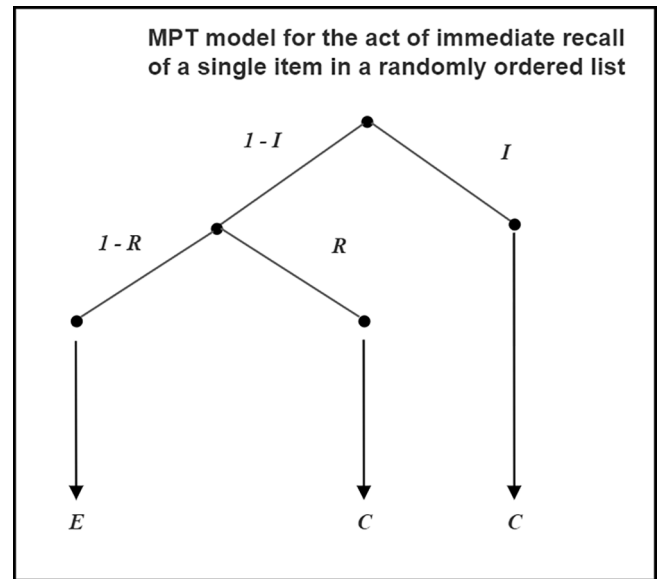


Fig. 2. An example of an MPT model showing the act of immediate recall of a single item in a randomly ordered list. (Adapted from Schweickert (1993)).

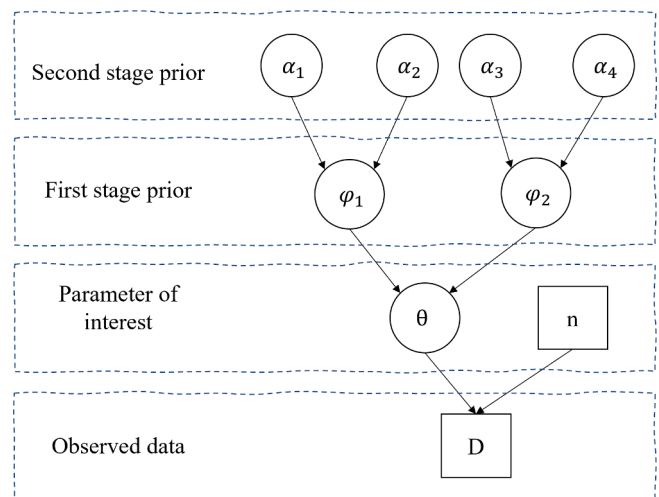


Fig. 3. Directed acyclic graph of Bayesian inference with hierarchical structure.

from the previous step. The Bayesian inference approach is then integrated with the MPT model to obtain the analysis results. Finally, the results are compared to select the most suitable modelling language.

Step 1: Describe the system and the scope of the analysis

The first step of the framework is to define the system and the scope of the analysis, which includes the description of the system, the purpose of modelling, and end-users of the developed models. If the system boundaries and purpose of modelling are not well-defined initially, the study can be inconsistent and generate irrelevant results rather than the value. The description should include the following:

System description: Description of the system and its operation to be modelled, “What will be modelled?”.

Purpose: Aim of the application, “Why will it be modelled?”.

Relevant stakeholders: Selection of relevant end-users that will evaluate and compare the modelling languages, “For whom will it be modelled?”.

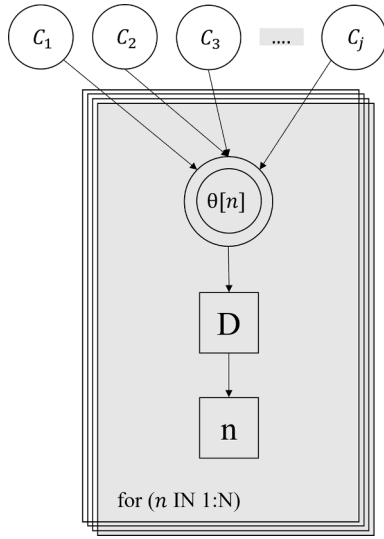


Fig. 4. A graphical model of Bayesian inference for the modelling language assessment MPT model (BahooTorood et al., 2020).

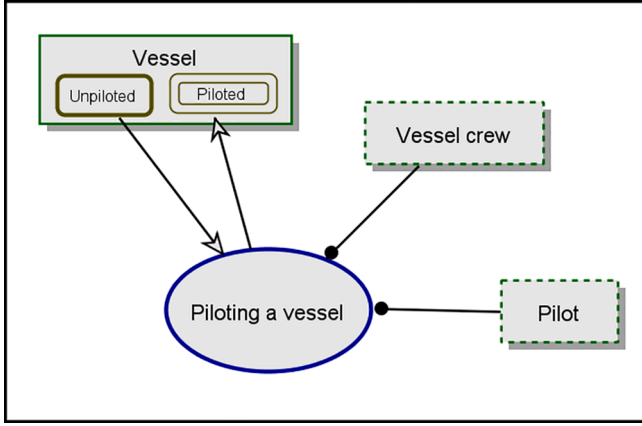


Fig. 5. OPD diagram showing the abstract view of ship pilotage and its components.

Step 2: Select relevant comparison criteria and candidate modelling languages

The modelling languages can be compared based on different criteria related to their features. Table 1 and Table 2 provides a list of common comparison criteria related to the usefulness and ease of use of MBSE language respectively. These criteria were identified by reviewing existent MBSE literature, frameworks, and comparison studies, which indicate important user-related features of the modelling languages. These features vary between different modelling languages. For example, some modelling languages can provide simulation features supporting even complex systems, while some provide none or only low support, which can still be useful for simple systems.

Among the criteria presented in Table 1 and Table 2, the end-users should identify the features of the modelling languages that are relevant and needed for their tasks. For example, a risk analyst would require diagrams that show the structure, function and interactions of the system components for identifying potential hazards. As a result, the features: structural modelling and behavioural modelling should be included as criteria to select a suitable modelling language for the risk analyst. To frame a concrete and efficient MCDM, herein, the most relevant criteria are accounted for the establishment of methodology. This reduces the time and effort required to evaluate the system

modelling languages. Based on the selected relevant criteria, literature review, and available resources, the system engineers should then narrow down the number of candidate modelling languages. These candidate modelling languages should then be implemented and compared in the following steps.

Step 3: Model a part of the system using MBSE modelling language

Next, the candidates of modelling languages in step 2 should be applied in a part (subsystem or component) of the system. All stakeholders/end-users defined in the first step, need to participate during the modelling process to get familiar with the models and understand their benefits and limitations. Furthermore, the participants should also ensure that the part (sub-system) selected for the application is not highly simple when compared with the level of complexity of the whole system.

Step 4: Determining end-user's perceived usefulness and ease of use

After the modelling process, the end-users should evaluate each of the implemented modelling languages in terms of perceived usefulness and ease of use. For the evaluation of each criterion, the questionnaire in Appendix A. is formulated and answered by the end-users using the provided rating scale. Table 3 shows the rating scale used in this study, which is a common 5-point Likert scale recommended by Dawes (2008).

Step 5: Update the MPT model with observed data

All ratings, as mentioned above, have a chance to be assigned by the end-user as the appropriate rate for evaluating the given MBSE language criteria. The probability that a certain rating is given to an MBSE language criteria is always mutually exclusive with other ratings. These independent probabilities can be modelled through a categorical distribution, i.e., Multinomial Process Tree (MPT). Based on the steps followed in the assessment process, an MPT should be developed. An MPT consists of a set of branches (denoted by $Z_{ij}, i = 1, 2, \dots, I_j$) terminating in categories $C = \{C_1, C_2, \dots, C_j\}$ through I_j paths. A schematic MPT is illustrated in Fig. 3. Each branch has a probability of occurrence $\theta = \{\theta_1, \theta_2, \dots, \theta_s\}$ leading to a new condition for the development of MCDM for the selection of MBSE language. These probabilities are assumed to satisfy a functional form underlying parameters leading to a specific form for the probability of branches, given by (Abaei, et al. 2021);

$$P(Z_{ij}; \theta) = C_{ij} \prod_{s=1}^S \theta_s^{a_{ijs}} (1 - \theta_s)^{b_{ijs}} \quad (3)$$

where Z_{ij} represents the i th branch leading to category C_j , while C_{ij} is always a positive number, a_{ijs} and b_{ijs} are non-negative integers. Consequently, and based on the structure of the tree, the category probabilities are as follow (Abaei, et al. 2021);

$$P(C, \theta) = \sum_{i=1}^{I_j} P(Z_{ij}; \theta) \quad (4)$$

As a pre-condition for the final probabilistic structure of the model, the $\sum_j P(C_j, \theta) = 1$ should be satisfied for all processing branches, which allows each parameter to vary independently between [0,1]. For example, the MPT model in Fig. 2 shows the process of immediate recall of a single item in a randomly ordered list. In the figure, the recall leads to a correct category (C) if the trace is intact (I) or reconstructed (R); else, it will lead to an error category (E). (Schweickert, 1993)

Step 6: Employ Bayesian inference to the MPT model to obtain results

The Hierarchical Bayesian Model (HBM) is used to quantify the uncertainties associated with categorical random variables generated by

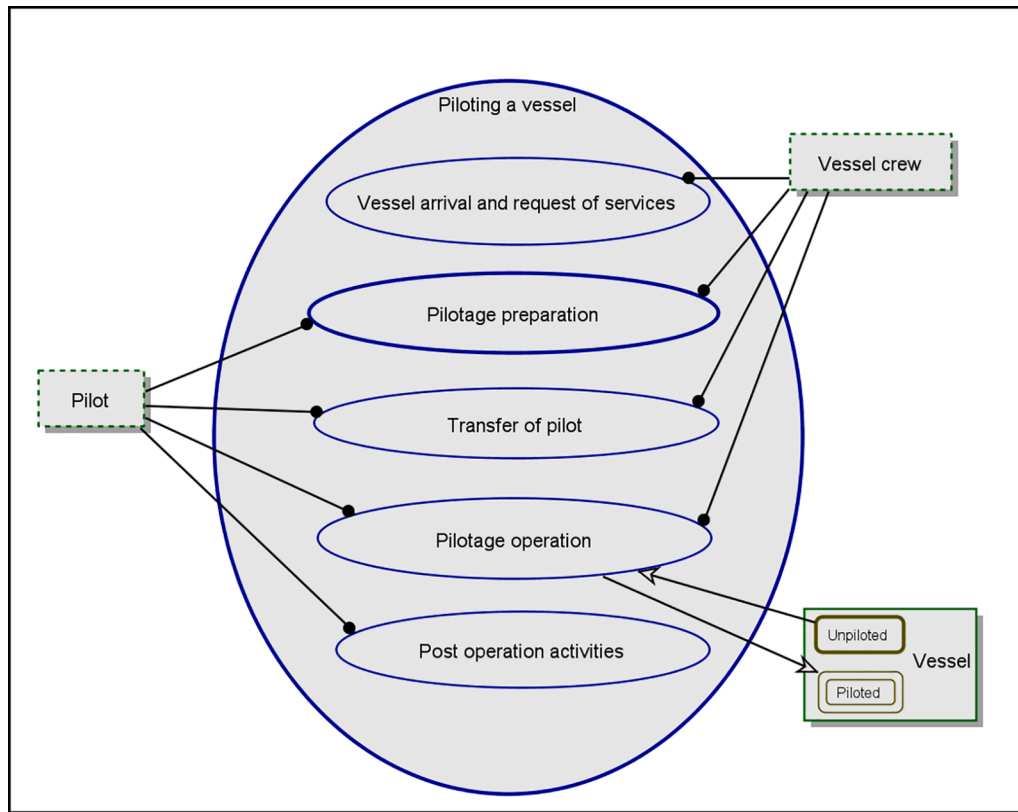


Fig. 6. OPM model presenting the sub-functions and components in ship pilotage.

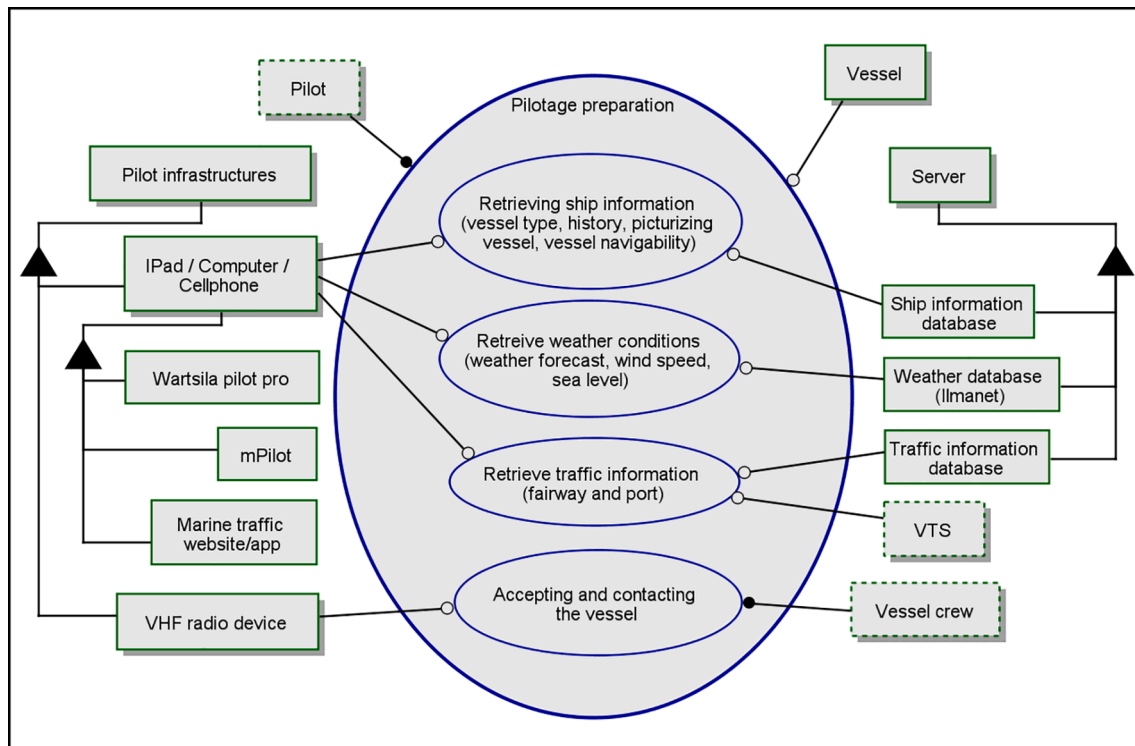


Fig. 7. In Zoomed OPM model presenting the components and process of pilotage preparation.

the MPT. The initial action toward the establishment of HBM, as demonstrated in the framework, is to assign a prior distribution for the parameter of interest, θ , using equation (2). Upon assigning the prior

distribution, a vector of hyper-parameters, φ , and its uncertainty, $\pi_2(\varphi)$ as the hyper-prior distribution needs to be sampled. A variety of prior distributions from non-informative to weakly informative and

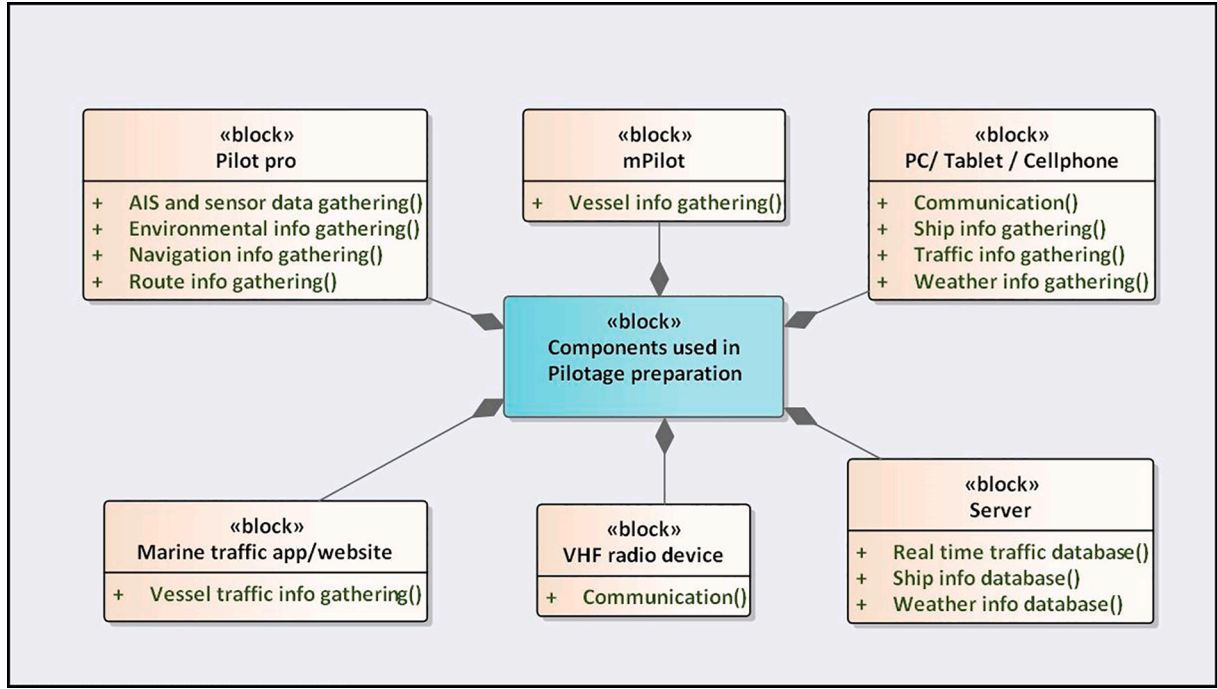


Fig. 8. SysML block definition diagram of components used in pilotage preparation.

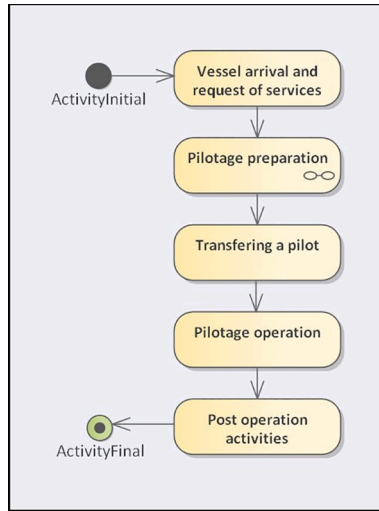


Fig. 9. SysML activity diagram presenting the sub-processes in ship pilotage.

informative prior can be sampled for hyper-parameters. The number of hyper-parameters is mainly dependent on the fitted probability distribution function for the parameter of interest, θ (e.g., θ with a normal distribution $(\theta | \mu, \sigma^2)$) will have two hyper-parameters of mean and standard deviation). Fig. 3 presents the hierarchical structure of Bayesian inference through the parameter of interest of a multinomial distribution, θ , and hyper-parameters. As it can be seen in this Figure, two hyper-parameters, φ_1, φ_2 , are governing the prior probability distribution of θ , each of which is modelled by another set of hyper-parameters; (α_1, α_2) are assigned to describe φ_1 , and (α_3, α_4) for modelling, φ_2 . There are three levels of hierarchy with two stages of prior; the first stage prior as $\theta | \varphi_1, \varphi_2$, and the second stage prior as $\varphi_1, \varphi_2 | \alpha_1, \alpha_2, \alpha_3, \alpha_4$. Presenting the population variability for θ by the first and second stage priors is the third step. It is then followed by formulating the likelihood function of a parameter of interest given observed data as below (Abaei, et al. 2021);

$$f(n, k | C, \theta) = \left(\frac{n}{k_{j1}, \dots, k_{jk}} \right) \prod_{k=1}^k [P(C_{jk} | \theta)^{n_{jk}}] \text{ for } j^{\text{th}} \text{ Likert scale} \quad (5)$$

Finally, the last two steps of calculating the posterior probability distribution of hyper-parameters and parameter of interest can be executed given the Bayesian theorem stated by equation 1.

The resulting directed acyclic graph model for established HBM is illustrated in Fig. 4 in which C_j are categories and θ represents the probability of occurrence. The circles and double circles display the uncertain parameters and uncertain categorical variables. D denotes the aggregated count data for any questionnaire thus follow Multinomial (θ, n) , where n is the total number of end-users answering the questionnaire.

Step 7: Compare inferred results and select the most suitable method

Using the Bayesian inference on the observed data, the probability of end-users selecting each of the categories can be identified. The language with a better probability of end-users selecting category 4 (agree with the questionnaire) and category 5 (strongly agree with the questionnaire) should be selected. Furthermore, the probability of end-users familiarizing themselves and recalling the features of modelling language should also be observed before making the final selection.

3. Results – Application of framework in ship pilotage operation.

3.1. Background and purpose of the case study

The developed framework is examined through a study of ship pilotage operation to select a suitable modelling language for creating system description models. The Pilotage act by the Ministry of Transportation and Communications (2003) defines pilotage as “the operations related to the navigation of ships in which the pilot acts as an advisor to the master of the ship and as an expert on the local waters and their navigation.” When navigating in a congested water area, the pilot boards the ship and provides necessary advice to the master for safer

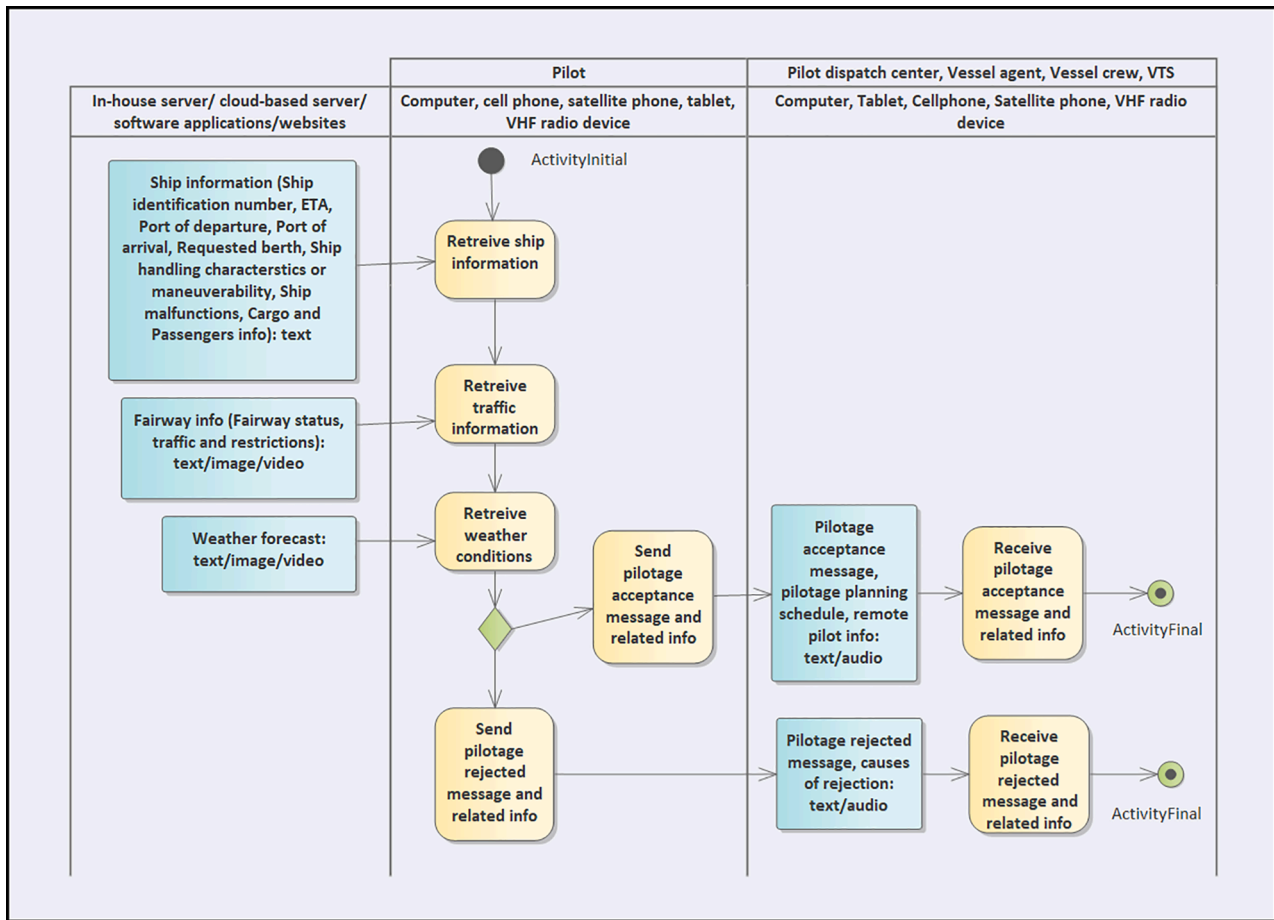


Fig. 10. SysML activity diagram presenting the components, stakeholders, and interactions during pilotage preparation.

navigation. Although the pilotage improves vessel traffic safety in congested waterways, several accidents still occur during the pilotage process (Park et al., 2019). Furthermore, the usage of new technology and the development of remote pilotage has increased the overall complexity of ship pilotage operation. Modelling such a complex system with a high number of components and interactions will require the application of MBSE modelling languages due to the benefits they offer as described in the previous sections. To select the most suitable modelling language for the remote pilotage, the proposed MCDM-based framework will be applied to a part of the ship pilotage operation.

3.2. Demonstration of the proposed framework

Step 1: Describe the system and scope of the analysis

This modelling language application aims to create a system description of pilotage operation that helps the stakeholders to understand the components, processes, and interactions involved in ship pilotage. This will further allow conducting several analyses such as risk assessment, design comparison, and cost-benefit analysis of ship pilotage operation.

Ship pilotage operation consists of several sub-operations such as Vessel arrival, Order of services, Pilotage preparation and Pilotage operation. For the demonstration of the proposed framework, the scope of the analysis was set to the sub-process: pilotage preparation. The pilotage preparation process was selected because it is one of the major tasks in remote pilotage with sufficient complexity and includes most of the components used in pilotage operation.

As the end-users of the system models are pilots and pilotage company stakeholders, 3 pilots and a technology manager of a pilotage company were invited to conduct this case study. The selection of the

participants was conducted based on their experience (over 5 years) and knowledge of ship pilotage.

Step 2: Identify relevant criteria and candidate modelling languages

After establishing the analysis scope and context, the applicable comparison criteria were selected by end-users based on the importance of the MBSE features in their work. These criteria were selected from the list of criteria presented in Table 1 and Table 2 in Section 2. The comparison criteria selected for this case study are as follows:

1. Structural modelling: Presenting the system composition such as components list, hierarchy, and internal structure.
2. Behavioural modelling: Presenting the system behaviour such as components functions, change of states, information exchange, command exchange and other interactions.
3. Traceability: Linking different types of system models for easier navigability and access to related information (defining the sources, targets, and relationships).
4. Resources requirement: Amount of resources required for modelling.
5. Communication: Exchange of information between stakeholders.
6. Modelling complexity: Difficulty in creating or interpreting the system models.
7. System complexity management: Features to manage the system complexity such as system decomposition and abstraction levels.

According to the end-users in this study, the first three criteria (1) structural modelling, (2) behavioural modelling and (3) traceability) were selected because, when identifying the hazards in pilotage operation, the end-users need to understand the components, functions, interactions, and the links between different diagrams. Furthermore, the

Table 4

Questionnaire for determining the Perceived Usefulness (PU) of modelling languages.

Features	Survey items	Rating (Ra)
Structural modelling	1. The method effectively presents the components of the system.	
	2. The method effectively presents the internal layout of the components.	
Behavioural modelling	3. The method effectively presents the component functions.	
	4. The method effectively presents the state change of components.	
	5. The method effectively presents the exchange of information and commands between components.	
	6. The method effectively presents the interactions with external components such as the environment.	
Requirements analysis	7. The method highly supports the analysis of system requirements.	
Engineering analysis	8. The method highly supports the analysis of the physical and performance of a system (i.e. efficiency, power, trade-off and cost-benefit analysis)	
Simulation	9. The method effectively simulates the system behaviour.	
Traceability	10. The method highly supports the traceability between the model elements (i.e. between different types of diagrams, level of abstraction, level of components hierarchy)	
Resources requirement	11. The modelling process does not require high resources (i.e. time and finance).	
International standard	12. The method has high international recognition such as ISO.	
Communication	13. The results can be easily communicated across various stakeholders (documents, diagrams, online, offline etc.).	

Table 5

Questionnaire for criteria related to Ease Of Use (EOU) of methods.

Features	Survey items	Rating (Ra)
Modelling Complexity	1. It is easy to interpret the models after initial training.	
	2. It is easy to create the models after initial training.	
System complexity management	14. The model management features help to manage highly complex systems (high number of components, functions and interactions).	
Training support	15. The initial training process is not intensive and does not require high mental and physical efforts.	

(4) resources requirement was selected because of the limitation of resources within the company and (6) modelling complexity was selected as a high number of the pilotage end-users lack a technical background. As the recent developments in pilotage such as remote pilotage has increased the system complexity, the (7) system complexity management criterion was added as relevant criteria for the comparison. Finally, the (5) communication criterion was selected because these diagrams are planned to be shared between all different groups of stakeholders within the company. Several modelling languages literature was then reviewed to narrow down the number of candidate modelling languages. Based on the selected criteria and available resources, two candidate modelling languages, Object Process Methodology (OPM) and System Modelling Language (SysML) were then selected for the assessment.

Table 6

A sample questionnaire rating provided by a pilot for SysML.

Questionnaire (SysML)	End-user's rating
The method effectively presents the components of the system. (structural modelling)	4 = Agree
The method effectively presents the system function. (behavioural modelling)	4 = Agree
The method effectively presents the exchange of information, interactions, and commands between system components. (behavioural modelling)	4 = Agree
The method supports the traceability between the model elements (i.e., different types of diagrams, level of abstraction, level of components hierarchy) (Traceability)	5 = Strongly agree
The modelling process does not require high resources (i.e., time, human, and finance) (resources requirement)	4 = Agree
The results can be easily communicated across various stakeholders. (communication)	4 = Agree
It is easy to interpret the models after initial training. (Modelling complexity)	4 = Agree
The model management features help to manage highly complex systems (System complexity management).	4 = Agree

Step 3: Model a part of the system using MBSE modelling language

Next in a modelling session with end-users, the OPM and SysML were implemented in the pilotage preparation process. The elements used in each language and the process of modelling were first described to the end-users, and then the pilotage preparation process was modelled with end-users participation. At first, the OPM models were created using OPCAT software. Fig. 5 shows the main Object Process Diagram (OPD) at the highest abstract level. The primary process, which is “piloting a vessel” is shown in an oval shape, while the components in rectangular. Next, Fig. 6 shows an In Zoomed OPD, which provides more detail about ship pilotage by presenting the sub-processes. As shown in the figure, the sub-processes in piloting a vessel are vessel arrival and request of services, pilotage preparation, transfer of pilot, pilotage operation and post-operation activities. Similarly, Fig. 7 shows the In Zoomed OPD of sub-process, Pilotage preparation, which was selected as a scope for this demonstration as specified in Step1. This OPD shows in detail the functions inside the pilotage preparation, the components involved during the process, and their interaction sequence. The figure shows that the pilotage preparation begins with the pilot retrieving the ship information from a database located at a pilotage company server. Similarly, the weather conditions and traffic information is retrieved from the available database. The information is retrieved using either a tablet, computer, or cell phone through applications such as Pilotpro, Mpiot, and Marine traffic websites. The process then ends with a pilot contacting the vessel crew and accepting the pilotage request using a radio device.

Following the OPM modelling, the SysML was then applied to create the system description of the sub-process (pilotage preparation) using Enterprise Architect software. First, the block definition diagram, as shown in Fig. 8, was developed. This diagram shows the components used in the pilotage preparation task and the functions of each component. The components shown in the diagram are Pilot pro, Mpiot, Marine traffic app/website, PC, Tablet, Cellphone, VHF radio device, and a server. The pilotage process was then modelled using activity diagrams. Similar to the OPM model, the higher abstraction level activity diagram was created first to show the sub-processes of remote pilotage, which are vessel arrival and request of services, pilotage preparation, transferring of a pilot, pilotage operation and post-operation activities as shown in Fig. 9. Then another activity diagram was developed for the pilotage preparation sub-processes, which shows the sequence of actions, components, and stakeholders involved during the pilotage preparation process as shown in Fig. 10.

Step 4: Determine end-user's perceived usefulness and ease of use

After modelling the pilotage preparation process, the end-users were

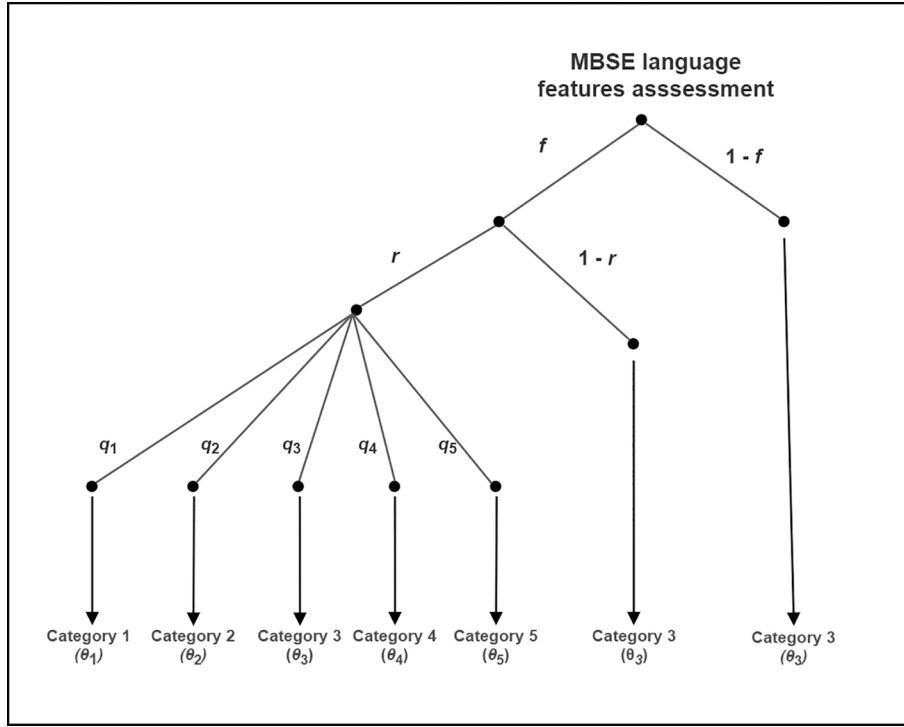


Fig. 11. A multinomial process tree model denoting the process followed during the assessment of each criterion of the SysML and OPM. The $\theta_1 - \theta_5$ denotes the probability of end-users providing rating 1 (Strongly disagree) – 5 (Strongly agree) to the q.

asked to provide ratings about the usefulness and ease of use of each method, SysML and OPM. The questionnaires shown in Table 4 and Table 5 was used to collect the ratings. A sample questionnaire from one of the pilots in the case study is shown in Table 6.

Step 5: Update the Multinomial process tree (MPT) model with observed data

Based on the steps followed in the assessment process, an MPT was developed and illustrated in Fig. 11. Accordingly, the obtained data from Step 4 were then adopted in the developed MPT model. This model denotes the process followed by the end-users during the assessment process until providing the questionnaire ratings. As the process followed was the same for all the criteria, the same tree model can be used for the assessment. The $\theta_1 - \theta_5$ denote the probability that end-users providing rating 1 (Strongly disagree) – 5 (Strongly agree) to the questionnaire, respectively. The f denotes the probability that end-users being familiarized with the features of each modelling language, whereas r denotes the probability of end-users being able to recall the familiarized features. The θ_3 denotes the 3rd category (3 - Undecided) where the end-users could not decide the answer for the questionnaire. As shown in Fig. 3, if the end-users are not able to be familiarized with the modelling language features or recall the features then the outcome would be θ_3 .

Step 6: Employ Bayesian inference to the MPT model to obtain results

Based on the developed MPT model, Bayesian inference is applied to obtain the probability distribution of the MPT variables. Given independent branches, the probability for each of the response categories ($\theta_1 - \theta_5$) is achieved by the summation of branch probabilities terminating to its category using equation (6):

$$P(C_k|\theta) = \sum_{i=1}^{I_k} C_{ik} \prod_{s=1}^S \theta_s^{a_{iks}} (1 - \theta_s)^{b_{iks}} \quad (6)$$

For example, The MPT model shows that the probability of θ_1 (i.e. end-users selecting strongly disagree with the questionnaire) requires

end-users to be familiarized with the features of the modelling language, and also to be able to recall the features and finally to select the first category. As Bayesian theorem requires prior distribution of the parameters f , r and q , the $Beta(\alpha, \beta)$ prior distribution with $\alpha = 1$, $\beta = 1$ is adopted as a non-informative uniform prior. This non-informative prior distribution has been assigned since there is no support with either expert's judgement or historical data under the same condition for the aforementioned variables (f, r, q). The only available data is the opinion of experts on branch probabilities, θ . The aggregated count data, k , for any questionnaire follow Multinomial distribution (θ, n), where n is the total number of end-users answering the questionnaire. The Bayesian model for the developed MPT is shown in Fig. 4.

Accordingly, using Bayesian inference and through the application of two modelling languages of SysML and OPM, the posterior probability for each of the categories and criteria were estimated. To estimate the posterior distribution of the parameter of interest, the MCMC simulation from prior distribution and likelihood function was executed. Through this simulation, three chains with over-dispersed initial values of $\theta_1, \theta_2, \dots, \theta_5$ were used. As stated by Kelly et al. (2009), running two chains are enough to calculate the posterior distribution of the parameters, however, this study conducted based on three chains aids in confirming the calculations by checking the convergence of the applied chains. Further to this confirmation, over-dispersed initial values were considered in MCMC simulation to ensure the validity of the estimation of the posterior distribution. It means that if the chains with different starting values can reach the same location of the posterior mode, the estimated posterior values are valid and confirmed. Accordingly, 1000 burn-in iterations of Monte Carlo estimation were applied to burn-in the three chains followed by 300,000 iterations. To confirm the calculations in the developed Bayesian-based model, the convergence check has been executed for all the parameters and variables, however, because of limited space, here only the trace plot and history of calculations of one of the categories (θ_1) for one criterion (structural modelling) through one of the languages (SysML) is illustrated in Fig. 12. Three colours in Fig. 12 are representing the track of the three mentioned chains with different initial values through the MCMC simulation. As it can be seen,

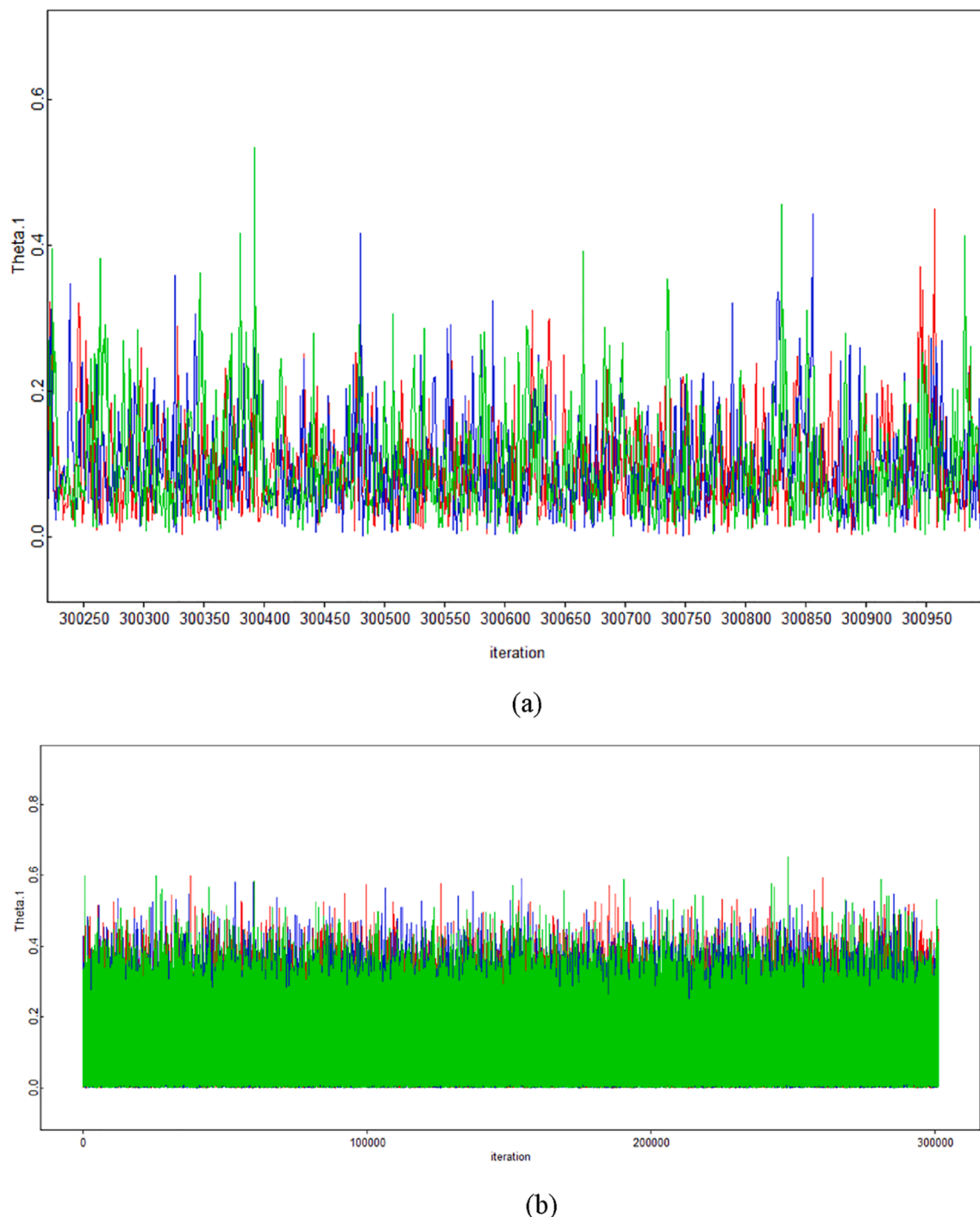


Fig. 12. Trace plot (a) and iterations history (b) of MCMC simulation for (θ_1) based on structural modelling through SysML language.

three chains are well-mixed proving the convergence to the location of posterior mode. This convergence is verifying the stability and robustness of the executed model.

Step 7: Compare inferred results and select the most suitable method

Fig. 13 presents the estimated posterior probability for each of the categories and criteria. In addition, Fig. 14 outlines the predictive posterior probability of categories meaning which categories would be chosen most by general end-users for two employed languages. The prediction has been carried out for all criteria, though due to limited space, only structural modelling, modelling complexity, and system complexity management are illustrated. Fig. 15 reports the predictive

posterior probability of these two categories for all criteria of SysML and OPM. As presented here, it is predicted that the SysML will have a higher agreement by end-user through all given criteria in this study. Based on these comparisons, SysML was selected as the most suitable method for detailed modelling of pilotage operation.

4. Discussion

4.1. The framework

The proposed framework provides a systematic approach to identify a suitable modelling language for complex systems and operations. The

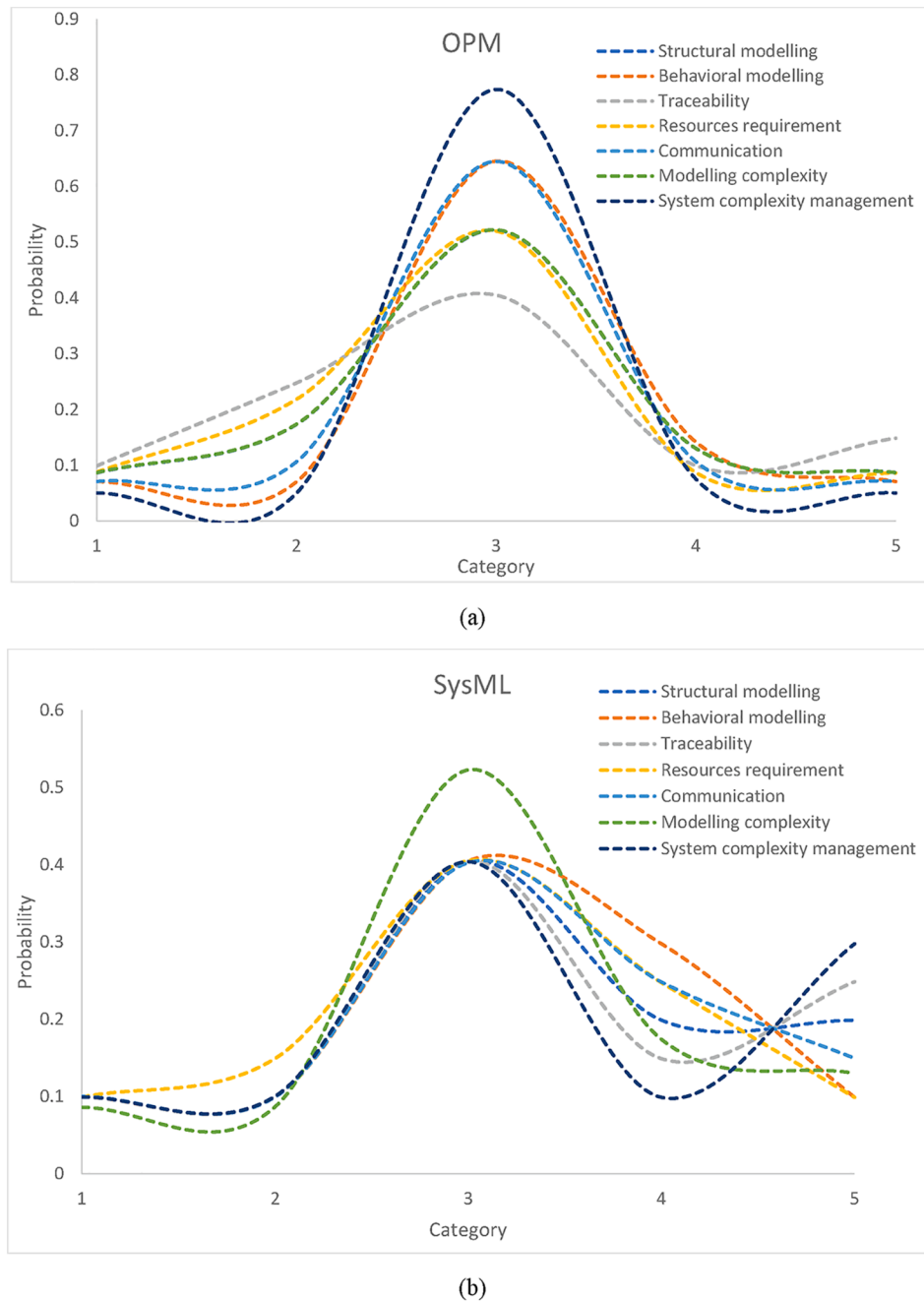


Fig. 13. Estimated categorical probability based on different criteria for OPM (a) and SysML (b).

difference in creating and understanding the models using different modelling languages can be a minor issue for system engineers but it can be a major issue for the other end-user groups such as technology providers, operators and management. The end-users with non-technical backgrounds have to invest high effort in interpreting the developed models and utilizing the models for their tasks. The required effort varies between different modelling languages. This was also concluded from the case study as the selected end-users preferred SysML over OPM for the description of pilotage operation. Thus, one of the strengths of the developed MCDM framework is the capability to integrate the perception of different types of end-users in the process of selecting the MBSE language. Furthermore, the questionnaire developed using TAM principles allows easier integration of end-user's perception by identifying the perceived usefulness and ease of use of each modelling language.

While the MBSE comparison framework provided by Weilkens et al.

(2016) can evaluate different MBSE methodologies, the authors mentioned that the results of the study can be interpreted differently by various users. Thus, the study concluded that instead of self-assessment, the inclusion of evaluations and feedback from independent users will improve the robustness and neutral assessment of the proposed framework. A similar conclusion was also provided by Grobshtein et al. (2007) when comparing different MBSE methods as the authors concluded that both methods have their advantages and disadvantages depending on modelling purpose and the end-users. The MCDM framework proposed in this study covered these gaps by integrating the end-users throughout the modelling, comparison, and selection process. Based on the purpose of system modelling, the comparison criteria are also selected by the end-users so that only the relevant criteria are assessed and evaluated for the final selection.

There are several other MCDM frameworks with different data-

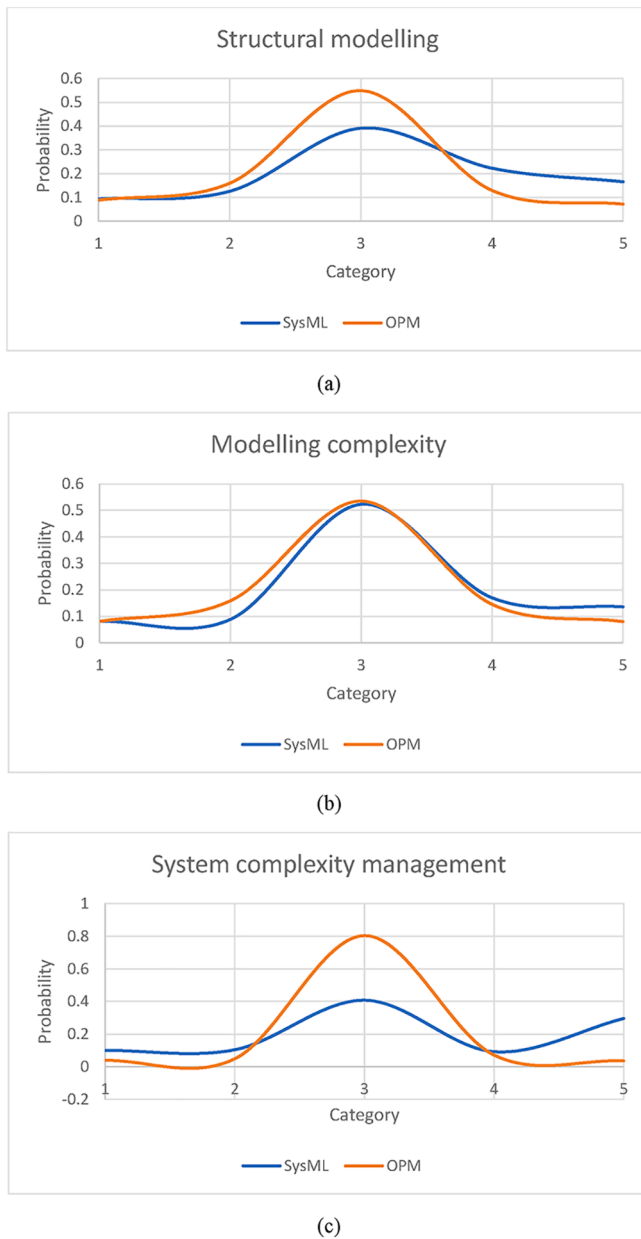


Fig. 14. The categorical predictive posterior probability of structural modelling (a), modelling complexity (b), and system complexity management (c) for SysML and OPM.

analysis and decision-making techniques, such as Grey-point-allocation full-consistency (Grey-PA-FUCOM), Fuzzy model, and Analytical Hierarchical Process (AHP). However, the proposed MCDM framework in this study employed a novel combination of MPT and Bayesian inference for the data analysis and decision-making because of its additional benefits and suitability to the criteria rating process. The application of MPT modelling in the MCDM framework enabled the study of the influence of end-user's cognitive process in the selection of categorical answers. The developed MPT model shows that the end-users selecting category 3 (Undecided) as an answer was more likely than other categories because of 3 different paths leading to category 3 in comparison to a single path for other categories. Furthermore, even with limited data, the Bayesian inference allowed the estimation of the posterior probabilities of end-users selecting different categories for the candidate modelling languages (SysML and OPM). The results of this study further strengthen the suitability of using the combination of MPT and Bayesian inference for decision-making, which has been also concluded by other

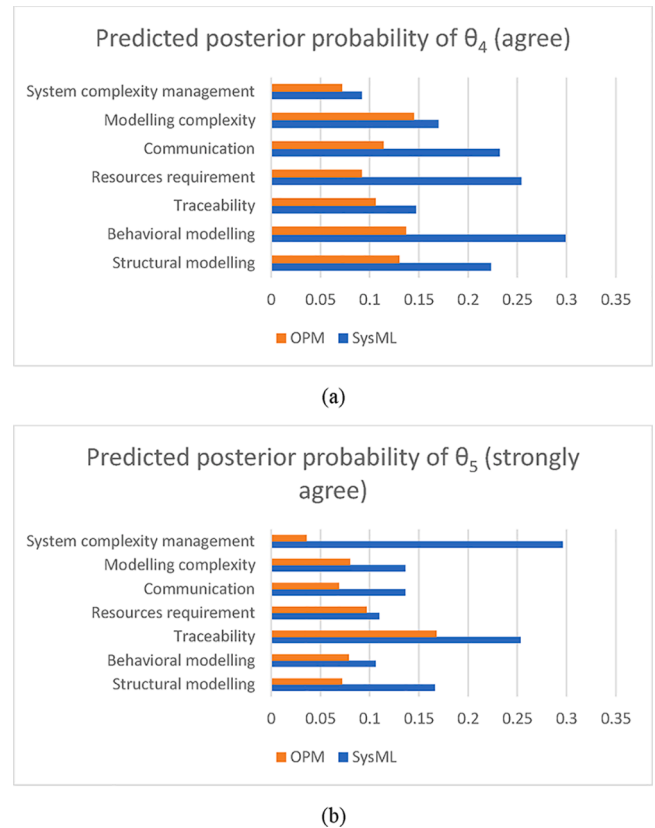


Fig. 15. Predicted posterior probability of fourth (a) and fifth category (b) for all given criteria through SysML and OPM.

recent studies such as, Abaei et al. (2021) and Lee et al. (2020).

Applying the framework to assess and select a suitable modelling language required additional efforts from the end-users. Although the omission of irrelevant comparison criteria in Step 2 of the framework reduced the necessary resources, the execution of each step still required time and effort from end-users. However, the resources required for the selection process are trivial compared to the resources invested in the detailed modelling. As a result, opting for another modelling language after the detailed modelling phase is not a viable option. Furthermore, the additional effort invested in the modelling language selection process will help end-users familiarize themselves with the MBSE modelling languages, which is essential and of high value for complex system operations. It should be considered that the list of comparison criteria can still be expanded as there can be several criteria that are specific for companies or application contexts. However, providing the complete list of MBSE comparison criteria is out of scope for this paper. Thus, the list only includes the common comparison criteria related to end-users as identified during the literature review. As the increase of comparison criteria in the assessment also requires additional resources, a balance between the number of comparison criteria and available resources should be considered to achieve maximum effectiveness.

4.2. The case study

The case study results show that in ship pilotage operation, the probability of end-users selecting category 3 (undecided) is the highest among all categories. For the other four categories, the results varied between different criteria. However, it can be seen that SysML mostly had a higher probability of an end-user selecting category 4 (agree) and category 5 (strongly agree), whereas OPM had a higher probability of an end-user selecting category 1 (strongly disagree) and 2 (disagree). The results also suggest that in the case of ship pilotage operation, SysML has

a better probability for most of the criteria. These included the effectiveness in presenting the components, functions, exchange of information and interactions between system components, providing traceability between the model elements and communication of results than OPM. Moreover, the resource requirement, modelling complexity and system complexity management were also deemed better with SysML than OPM. It is worth mentioning that some of the symbols and notations in SysML were similar to the flow chart diagrams that the end-users had already used before, which might be one of the reasons that they found SysML diagrams easier to understand. Consequently, and based on the results for the selected group of end-users, SysML is selected to be implemented for the detailed modelling of ship pilotage operation.

As presented by Bayesian estimation in Fig. 15, while these two languages are predicted to have a quite similar categorical probability for modelling complexity, there are striking differences, especially in the fourth and fifth categories, through structural modelling and system complexity management. It is necessary to note that the responses of categories 4 and 5 were the focus of the analysis because they reflect the suitability of the MBSE modelling.

The case study was easily conducted by following the systematic steps as outlined in this paper. Although the number of end-users was less in the case study, the usage of Bayesian inference enabled the estimation of the probability of end-users selecting different categories. Furthermore, the inferred results allowed easy comparison and evaluation of SysML and OPM, thus enabling the decision to select SysML for detailed modelling of pilotage operation. Although the number of participants was enough to demonstrate the framework in this study, a higher number of end-users for selecting the modelling language could result in more reliable data, which affects the final selection of the modelling language. In addition to the end-users, the number of candidate modelling languages could have been also increased. The selection of the modelling language for the case study was limited to SysML and OPM. Increasing the number of candidates modelling language could provide more options to the end-users for the assessment and selection for pilotage operation. However, the increment of end-users and candidate modelling language will also increase the required resources such as time and effort during the framework application process. Thus, the number of end-users and candidate modelling languages included in the assessment should be carefully considered depending on the available resources.

5. Conclusions

In contrast to the traditional approach, where system engineers are mainly responsible for the selection of MBSE language, the developed framework uses the inputs from all relevant users of the modelling language and its results. Moreover, the application of the proposed MCDM framework help project teams and companies to avoid loss of resources due to the change of modelling language midway through the project. Furthermore, the implementation of the framework also supports end-users to familiarize themselves with the system models and the modelling process. This familiarization can reduce the number of lessons and tutorials required for the end-users to be able to understand, interpret and utilize the system models for their tasks. Thus, the usage of the framework for the selection of modelling language can be of great importance for companies with complex projects.

The proposed framework uses the features of MBSE modelling languages as the comparison criteria and TAM for collecting and integrating the perception and beliefs of end-users in the selection process. While TAM is highly used to compare and assess modern against traditional methods, few studies have used TAM to compare different modern methods. This study strengthens the principles and usage of the TAM method in various domains. In addition to the proposed framework and the integration of TAM, the novelty of this study also lies in the application of MBSE modelling languages to the ship pilotage operation. In

this study, the pilotage preparation system models were developed and presented using OPM and SysML. Finally, a decision-making tool was developed using MPT and Bayesian inference, allowing the system engineers to compare the results and ease their selection predicament.

The selected method from the case study, SysML, will be applied next to a remote pilotage operation to develop the system description diagrams. The developed description of remote pilotage operation will then be used to conduct detailed risk management of the remote pilotage operation.

CRedit authorship contribution statement

Sunil Basnet: Conceptualization, Methodology, Software, Formal analysis, Resources, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ahmad Bahootoroody:** Methodology, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Meriam Chaal:** Methodology, Writing – original draft, Writing – review & editing, Investigation, Formal analysis, Visualization. **Osiris A. Valdez Banda:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Janne Lahtinen:** Investigation, Writing – review & editing. **Pentti Kujala:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- Abaei, M. M., Hekkenberg, R., & Bahootoroody, A. (2021). A multinomial process tree for reliability assessment of machinery in autonomous ships. *Reliability Engineering & System Safety*, 210, 107484. <https://doi.org/10.1016/j.res.2021.107484>
- Al-Fedaghi, S. (2014). Systems design: SysML vs. flowthing modeling. *International Journal of Software Engineering and Its Applications*, 8(1), 355–370. <https://doi.org/10.14257/ijseia.2013.8.110.14257/ijseia.2014.8.1.31>
- Amorim, T., Vogelsang, A., Pudlitz, F., Gersing, P., & Philipps, J. (2019). Strategies and Best Practices for Model-Based Systems Engineering Adoption in Embedded Systems Industry. *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*, 203–212. 10.1109/ICSE-SEIP.2019.00030.
- André, C., Mallet, F., & de Simone, R. (2008). Modeling AADL data communications with UML MARTE. In E. Villar (Ed.), *Embedded Systems Specification and Design Languages* (Vol. 10, pp. 155–168). Netherlands: Springer. https://doi.org/10.1007/978-1-4020-8297-9_11
- Anyanahun, A. I., & Edmonson, W. W. (2018). An MBSE conceptual design phase model for inter-satellite communication. *Annual IEEE International Systems Conference (SysCon)*, 2018, 1–8. <https://doi.org/10.1109/SYSCON.2018.8369575>
- Bahootoroody, A., Abaei, M. M., Bahootoroody, F., De Carlo, F., Abbassi, R., & Khalaj, S. (2019). A condition monitoring based signal filtering approach for dynamic time dependent safety assessment of natural gas distribution process. *Process Safety and Environmental Protection*, 123, 335–343. <https://doi.org/10.1016/j.psep.2019.01.016>
- Bahootoroody, A., De Carlo, F., Paltrinieri, N., Tucci, M., & Van Gelder, P. H. A. J. M. (2020). Bayesian regression based condition monitoring approach for effective reliability prediction of random processes in autonomous energy supply operation. *Reliability Engineering & System Safety*, 201, 106966. <https://doi.org/10.1016/j.res.2020.106966>
- Baklouti, A., Nguyen, N., Mhenni, F., Choley, J.-Y., & Mlika, A. (2019). Improved Safety Analysis Integration in a Systems Engineering Approach. *Applied Sciences*, 9(6), 1246. <https://doi.org/10.3390/app9061246>
- Basnet, S., Valdez Banda, O. A., & Chaal, M. (2019). *Comparison of system modelling techniques for autonomous ship systems*. 125–139.
- Batchelder, W. H., & Riefer, D. M. (1986). The statistical analysis of a model for storage and retrieval processes in human memory. *British Journal of Mathematical and*

- Statistical Psychology, 39(2), 129–149. <https://doi.org/10.1111/j.2044-8317.1986.tb00852.x>
- Batchelder, W. H., & Riefer, D. M. (1990). Multinomial Processing Models of Source Monitoring. *Psychological Review*, 97(4), 548–564.
- Batchelder, W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modeling. *Psychonomic Bulletin & Review*, 6(1), 57–86. <https://doi.org/10.3758/BF03210812>
- Jacucci, E., Benbya, H., & McKelvey, B. (2006). Toward a complexity theory of information systems development. *Information Technology & People*, 19(1), 12–34. <https://doi.org/10.1108/09593840610649952>
- Best, B., Jurjens, J., & Nuseibeh, B. (2007). Model-Based Security Engineering of Distributed Information Systems Using UMLsec. *29th International Conference on Software Engineering (ICSE '07)*, 581–590. 10.1109/ICSE.2007.55.
- Chami, M., & Bruel, J.-M. (2018). A Survey on MBSE Adoption Challenges. 16.
- Chuttur, M. (2009). Overview of the Technology Acceptance Model: Origins. *Developments and Future Directions*, 25.
- Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results [Massachusetts Institute of Technology]. <http://hdl.handle.net/1721.1/15192>
- Dawes, J. (2008). Do data characteristics change according to the number of scale points used? an experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research*, 50(1), 61–104. <https://doi.org/10.1177/147078530805000106>
- Delligatti, L. (2014). *SysML distilled—A brief guide to the Systems Modeling Language*. Pearson Education.
- Dow, K. E., Wong, J., Jackson, C., & Leitch, R. A. (2008). A comparison of structural equation modeling approaches: The case of user acceptance of information. *Journal of Computer Information Systems*, 10.
- Esangbedo, M. O., Bai, S., Mirjalili, S., & Wang, Z. (2021). Evaluation of human resource information systems using grey ordinal pairwise comparison MCDM methods. *Expert Systems with Applications*, 182, 115151. <https://doi.org/10.1016/j.eswa.2021.115151>
- Estefan, J. A. (2008). *Survey of Model-Based Systems Engineering (MBSE) Methodologies*. 70.
- Fernandez, J. L., & Hernandez, C. (2019). *Practical model-based systems engineering*. Artech House.
- Friedenthal, S., Moore, A., & Steiner, R. (2015). *Practical Guide to SysML – The Systems Modeling Language (3rd Edition)*.
- Gough, K. M., & Phojanamongkolkij, N. (2018, June 25). Employing Model-Based Systems Engineering (MBSE) on a NASA Aeronautic Research Project: A Case Study. *2018 Aviation Technology, Integration, and Operations Conference*. 2018 Aviation Technology, Integration, and Operations Conference, Atlanta, Georgia. 10.2514/6.2018-3361.
- Grobshtein, Y., Perelman, V., Safra, E., & Dori, D. (2007). Systems Modeling Languages: OPM Versus SysML. *International Conference on Systems Engineering and Modeling*, 2007, 102–109. <https://doi.org/10.1109/ICSEM.2007.373339>
- Hallqvist, J., & Larsson, J. (2016). Introducing MBSE by using systems engineering principles. *INCOSE International Symposium*, 26(1), 512–525. <https://doi.org/10.1002/iis2.2016.26.issue-110.1002/j.2334-5837.2016.00175.x>
- Herzig, S. J. I. (2015). A Bayesian learning approach to inconsistency identification in model-based systems engineering [Georgia Institute of Technology]. <http://hdl.handle.net/1853/53576>.
- Hollnagel, E. (2012). *The Functional Resonance Analysis Method: Modelling Complex Socio-technical Systems*.
- INCOSE. (2007). *SEVision 2020*. http://www.ccoase.org/media/upload/SEVision2020_20071003_v2_03.pdf.
- Kalawsky, R. S., O'Brien, J., Chong, S., Wong, C., Jia, H., Pan, H., & Moore, P. R. (2013). Bridging the gaps in a model-based system engineering workflow by encompassing hardware-in-the-loop simulation. *IEEE Systems Journal*, 7(4), 593–605. <https://doi.org/10.1109/JSYST.2012.2230995>
- Karam, S., Nagahi, M., Dayarathna (Nick), V. L., Ma, J., Jaradat, R., & Hamilton, M. (2020). Integrating systems thinking skills with multi-criteria decision-making technology to recruit employee candidates. *Expert Systems with Applications*, 160, 113585. <https://doi.org/10.1016/j.eswa.2020.113585>
- Kaslow, D., Ayres, B., Cahill, P. T., Hart, L., & Yntema, R. (2017). Developing a CubeSat Model-Based System Engineering (MBSE) reference model—Interim status #3. *IEEE Aerospace Conference*, 2017, 1–15. <https://doi.org/10.1109/AERO.2017.7943691>
- Kelly, D. L., & Smith, C. L. (2009). Bayesian inference in probabilistic risk assessment—The current state of the art. *Reliability Engineering & System Safety*, 94(2), 628–643. <https://doi.org/10.1016/j.res.2008.07.002>
- Kongsberg. (2020). *HORIZON 2020: THE AUTOSHIP PROJECT HAS STARTED*. <https://www.kongsberg.com/maritime/about-us/news-and-media/news-archive/2020/autoship-programme/>.
- Kordon, F., Hugues, J., Canals, A., & Dohet, A. (2013). *Embedded Systems: Analysis and Modeling with SysML, UML and AADL*. Wiley.
- Lee, M. D., Bock, J. R., Cushman, L., & Shankle, W. R. (2020). An application of multinomial processing tree models and Bayesian methods to understanding memory impairment. *Journal of Mathematical Psychology*, 95, 102328. <https://doi.org/10.1016/j.jmp.2020.102328>
- Leoni, L., BahooToroody, A., Abaei, M. M., De Carlo, F., Paltrinieri, N., & Sgarbossa, F. (2021). On hierarchical Bayesian based predictive maintenance of autonomous natural gas regulating operations. *Process Safety and Environmental Protection*, 147, 115–124. <https://doi.org/10.1016/j.psep.2020.08.047>
- Levander, O. (2017). Autonomous ships on the high seas. *IEEE Spectrum*, 54(2), 26–31. <https://doi.org/10.1109/MSPEC.2017.7833502>
- Leveson, N. (2011). *Engineering a safer world: Systems thinking applied to safety*. MIT press.
- Mastrocinque, E., Ramírez, F. J., Honrubia-Escribano, A., & Pham, D. T. (2020). An AHP-based multi-criteria model for sustainable supply chain development in the renewable energy sector. *Expert Systems with Applications*, 150, 113321. <https://doi.org/10.1016/j.eswa.2020.113321>
- Michalkiewicz, M., Horn, S. S., & Bayen, U. J. (2020). Hierarchical multinomial modeling to explain individual differences in children's clustering in free recall. *Journal of Mathematical Psychology*, 98, 102378. <https://doi.org/10.1016/j.jmp.2020.102378>
- Ministry of Transport and Communications. (2003). Pilotage act 940/2003 (amendments up to 1534/2019 included). Finland.
- NASA. (2018). *Exploring the Value of MBSE at NASA*. APPEL Knowledge Services. <https://appel.nasa.gov/2018/06/08/exploring-the-value-of-mbse-at-nasa/>.
- Papanikolaou, A. (Ed.). (2019). *A Holistic Approach to Ship Design: Volume 1: Optimisation of Ship Design and Operation for Life Cycle*. Springer International Publishing. 10.1007/978-3-030-02810-7.
- Park, Y. A., Yip, T. L., & Park, H. G. (2019). An analysis of pilotage marine accidents in Korea. *The Asian Journal of Shipping and Logistics*, 35(1), 49–54. <https://doi.org/10.1016/j.ajsl.2019.03.007>
- Ponsard, C., & Landtsheer, R. D. (2010). *Comparison of the AADL and Event-B Model-Based Tool Chains for Designing Embedded Systems*. 9.
- Rahman, M. A. A., & Mizukawa, M. (2013). Model-Based Development and Simulation for Robotic Systems with SysML, Simulink and Simscape Profiles. *International Journal of Advanced Robotic Systems*, 10(2), 112. <https://doi.org/10.5772/55533>
- Reichwein, A., & Paredis, C. J. J. (2011). Overview of Architecture Frameworks and Modeling Languages for Model-Based Systems Engineering. *Volume 2: 31st Computers and Information in Engineering Conference, Parts A and B*, 1341–1349. 10.1115/DETC2011-48028.
- Rousseau, A., Halbach, S., Michaels, L., Shidore, N., Kim, Na., Kim, N., ... Kropinski, M. (2014). Electric Drive Vehicle Development and Evaluation Using System Simulation. *IFAC Proceedings Volumes*, 47(3), 7886–7891. <https://doi.org/10.3182/20140824-6-ZA-1003.02832>
- Sames, P. (2019). *Assurance of complex cyber-physical systems*. International Seminar on Safety and Security of Autonomous Vessels (ISSAV), Finland.
- Schweickert, R. (1993). A multinomial processing tree model for degradation and redeintegration in immediate recall. *Memory & Cognition*, 21(2), 168–175. <https://doi.org/10.3758/BF03202729>
- Solberg, C. L. (2018). *An STPA Analysis of the ReVolt*.
- Spyropoulos, D., & Baras, J. S. (2013). Extending design capabilities of SysML with trade-off analysis: Electrical microgrid case study. *Procedia Computer Science*, 16, 108–117. <https://doi.org/10.1016/j.procs.2013.01.012>
- Sulaman, S. M., Beer, A., Felderer, M., & Host, M. (2019). Comparison of the FMEA and STPA safety analysis methods—a case study. *Software Quality Journal*, 27(1), 349–387. <https://doi.org/10.1007/s11219-017-9396-0>
- Tepper, N. A. (2010). *Exploring the Use of Model-Based Systems Engineering (MBSE) to Develop Systems Architectures in Naval Ship Design* [Master's thesis].
- Vazquez-Santacruz, J., Torres-Figueroa, J., & Portillo-Velez, R. de J. (2019). Design of a human-like biped locomotion system based on a novel mechatronic methodology. *Concurrent Engineering*, 27(3), 249–267. 10.1177/1063293X19857784.
- Weilkiens, T., Scheithauer, A., Di Maio, M., & Klusmann, N. (2016). Evaluating and comparing MBSE methodologies for practitioners. *IEEE International Symposium on Systems Engineering (ISSE)*, 2016, 1–8. <https://doi.org/10.1109/SysEng.2016.7753174>