Applying Intelligence Amplification in Decision Making

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Abstract

This thesis explores the application value of intelligence amplification in decision making. The intelligence amplification (IA) highlights humans' central role in solving a problem. Instead of replacing humans with automation, IA amplifies humans' intelligence of solving a problem. IA emphasizes the strengths of humans and intelligent agents to overcome their respective limitations through the collaborative effort. In IA system, humans, as a guide, direct and supervise intelligent agents, while intelligent agents, as an assistant, aid humans to complete tasks efficiently and effectively

To apply IA in decision making, this thesis proposes an intelligence amplification (IA) framework. The IA framework introduces six steps of implementing IA in decision making: 1) analysis of decision making process, 2) identification of collaborative tasks, 3) task decomposition, 4) task assignation, 5) design of intelligent agents and 6) implementation.

With this IA framework, IA is applied to solve planning problems of synchromodal transport in the simulated environment. Through testing the usefulness of the designed intelligent agents that are built to cooperate with decision makers, the results validate the appropriateness of the task assignment instructed by the proposed IA model. It further helps to validate the practical applicability of the designed IA model in introducing IA to decision making.

The test results show that the collaborative effort of humans and intelligent agents makes a better decision on planning transportation activities than either humans or intelligent agents working alone. The results further indicate the potential practical value of IA in improving decision making on a real business case as well as amplifying decision makers' capability and performance of making decisions.

There is also a need to be aware of the potential challenges during applying IA into decision making. To achieve the expected IA effects, the specific decision making process should be defined according to a certain problem and the design of intelligent agents should pay special attention to the appropriate interaction design and the individual uniqueness.

Contents

List of Figures

List of Tables

1. Introduction

1.1. Research background

The capabilities of computers in calculating, data-processing, information storage and retrieval keep improving, which enables computers to outperform humans in majority of routine operations (Danson et al., 2015). For the last 50 years, computer scientists conducted research in the domain of Artificial Intelligence with the intention of creating computers and software capable of intelligent behavior. These intelligent agents are designed to act autonomously and exhibit human-like intelligence. But computers are designed primarily to solve pre-formulated problems based on available data according to predetermined procedures (Licklider, 1960). It is nearly impossible to foresee all problems in advance. However, there are other aspects like goals, business semantics, cultural idiosyncrasies, and sparks of creativity, that are difficult to be codified into machine language (Danson et al., 2015).

Entering the era of Big Data, the sheer volume and variety of data keep expanding due to the prevailing use of personal devices, the increasing numbers of open platforms and the vast variety of network systems. The more data we integrate from various sources and formats, the less effective data mining can be (Sankar, 2012). The massive unbounded data increases the complexity and difficulty of analytics, which could result in financial and intellectual frustration, confusion and exhaustion (Danson et al., 2015). Hence, even the advanced techniques can be distracting for decision making and will not give insights to people if these technologies are not properly applied.

1.2. Intelligence amplification

Hereby, it is time to reevaluate an alternative vision "instead of replacing human, computers collaboratively work with humans to amplify humans' intelligence of making effective decisions", which is Intelligence Amplification (IA).

IA was first mentioned by William Ross Ashby. Ashby (1956) claims that the intelligentual power is equivalent to the power of appropriate selection. That is, augmenting the power of selection improves the intelligence of problem solving. J.C.R. Licklider (1960) presents the idea of man-computer symbiosis. He argues that decisions should be made under the cooperation of humans and machines rather than depending on the predetermined programs, especially when it comes to complex situations. Due to the fact that either humans or computers, two different entities, perform some tasks better than the other, J.C.R.Licklider suggests to form the functions of humans and computers in a symbiotic partnership. This human-machine symbiosis relates with the task assignment problem from operations research: what kind of work should be assigned to men and what type of task should be completed by computers, in terms of the maximum efficiency and profit? In other words, the symbiotic relationship is to allow both men and computers to focus on the tasks that they are superior in. Douglas Engelbart (1995) also refers to IA for the goal of augmenting humans' intellect by organizing their intellectual capabilities into higher levels of synergistic structuring.

The viewpoints given by Ashby (1956), Licklider (1960) and Engelbart (1995) all emphasize humans' essential role in problem solving. Humans are flexible and capable of applying non-linear approaches to identify questions, iteratively hypothesize, discover new patterns, and pose a trait of creativity, which are very difficult for computers to replicate (Sankar, 2012). Licklider (1960) states that humans are superior in setting goals, formulating hypotheses, determining criteria, performing evaluation, and handling uncertainties. However, humans' capabilities are limited in coping with issues at scale, computation and volume. Hence in terms of efficiency, humans need computer to aid with the formulated and real-time thinking. Licklider (1960) suggests that computers do all the routine work to prepare humans for the insights to make a decision.

One of IA's traits is that IA amplifies humans' intelligence in dealing with complex issues. Specifically, IA allows humans to focus on a broader context while allowing technology to address standard rules that can be codified and executed autonomously. According to Sankar (2012), the potential application areas of IA will be extensive with data analytical applications. The medical community can identify the virus structure with the help of computer, and diagnose cancer by accessing as many patients medical record as possible. The intelligence community can inspect global calls, texts, and emails to identify possible terrorists or credit risk decisions. Police department can integrate and analyze data from multiple locals, states, and federal sources to conduct the crime analyst, resolving crime in real time. Farmers can use the data collected by their equipment, from almost every foot of each planting row, to increase crop yields. Risk and fraud detection, preventative maintenance, and productivity in supply chain are also viable candidates for applying IA (Danson et al., 2015).

Hereby there are great possibilities for IA to become critical for the competitive success in business. In the business world, decision making is a vital part as decision exists in all activities and functions of a business. The correct and appropriate decisions ensure the success of that business. However, it is not always easy to make the right decision because of uncertainties, the uniqueness nature of a problem, diverse goals, various stakeholders, and the lack of relevant information (McBurney, n.d.). Therefore, it is meaningful for this thesis to study whether and how IA can improve decision making to make a business competitive and successful.

1.3. Research goal

The goal of this thesis is to evaluate IA's practical value in improving decision making. In order to achieve this research goal, this thesis needs to find out an approach to implement IA.

The approach of applying IA into decision making in this thesis focuses on the business operations of decision making process. Business goals and requirements vary from organization to organization. Each business requires a variety of activities and methods to support the business requirements. In the meantime, each business scenario demands multiple data velocity, structure, and analytics complexity. Thus, the solution in this project aims to introduce a reference framework that guides IA practical application in decision making.

1.4. Research questions

The main research question of this thesis is:

How to apply intelligence amplification in decision making?

This question is divided into the following underlining questions, which need to be answered in order to provide an answer to the main research question:

1. What is the current state of the art in scientific literature?

    a. What is the current state of the art in scientific literature concerning the use of IA?
    b. What is the current state of the art in scientific literature on decision making?
2. What kind of IA framework is best suited for decision making?
    a. What kind of IA model/framework are available?
    b. What constructs should be included in the designed IA framework?
    c. What relationships between constructs should exist in the designed IA framework?
3. What are the advantages and disadvantages of applying the IA framework?
    a. How to apply the IA framework in simulated environment?
    b. What effects are produced by applying the IA framework in simulated environment?
    c. Do the effects prove that IA offers superior insights to decision making?
    d. To which extent is the IA framework applicable for a real case on different business areas and projects?

1.5. Research method

The design science research methodology (DSRM) (Peffers et al., 2007) is used to guide this thesis. There are three phases in this thesis: problem investigation, design and validation.

The first step is to define the research problem and justify the value of a solution, followed by defining the objectives of the solution (Peffers et al., 2007). The problem will be further investigated by the literature review. To conduct a thorough and structured literature review, the method of Webster and Watson (2002) is applied as the guide, together with the five-stage grounded theory method proposed by Wolfswinkel et al. (2013) for rigorously reviewing literature.

Then the artifact is designed to improve the problem context and satisfy the design requirements (Peffers et al., 2007). The artifact in this thesis is a framework that introduces the IA concept in decision making process.

Next is to validate the artifact in the problem context. The validation first needs to demonstrate how to use the designed framework to solve a problem. In this thesis, the validation method is a case study. Since the real-life context is complex and has many external influencing factors, the proposed IA framework will be validated in the simulated environment, a serious game about transport planning. The serious game allows to conduct testing in a simplified real-life context so that the validation of the application effects of the proposed IA framework can be completed effectively and efficiently.

Evaluation follows to measure how well the framework supports IA's application in decision making. In the end, this thesis communicates and discusses the results of validation, the artifact effectiveness, and the future improvement.

1.6. Thesis structure

Chapter 2 provides the findings from the literature review on the current state of the art in scientific literature concerning IA and decision making. Then Chapter 3 proposes the IA framework. Next, Chapter 4 introduces the serious game and describes how the IA framework works in the simulated environment. Chapter 5 then illustrates and discusses the validation results. Finally, the overall conclusion can be found in Chapter 6.

2. Literature review

This chapter provides a background on Intelligence Amplification (IA) and decision making, based on a systematic review of previous literature.

To conduct a thorough and structured literature review, this thesis uses the method of Webster and Watson (2002) as a guide, together with the five-stage grounded theory method proposed by Wolfswinkel et al. (2013) for rigorously reviewing literature. First step is to formulate questions that need to be answered through the literature review. Then a forward search is conducted with introducing the search query and selection process. Next, a short literature overview is presented. In the end, a *Backward Search* is conducted on the selected articles to get sufficient knowledge from the studied literature.

The search engine is SciVerse Scopus. The Scopus supports many search specification options and searches quickly through the world's largest database of title, abstract, and author information of leading scientific articles. Google Scholar is used to search for full text of the selected articles.

2.1. Intelligence Amplification (IA): A literature review

In this section, the IA concept is investigated. First, the overview of literature search and selection process is presented. In the second part, the role of human in IA system is discussed, followed by the description of relationship between humans and intelligent agents. Then the application of IA is discussed and finally the frameworks/frameworks of applying IA are introduced.

2.1.1. Literature search and selection process

Based on the research goals and the research questions, it is necessary to find out what has been studied about the intelligence amplification (IA) by answering the following knowledge questions.

1. What is the role of human in IA system?
2. What is the relationship between humans and intelligent agents?
3. What is the application of IA? What are the benefits of applying IA?
4. What kind of model / framework is mentioned for application?

This thesis uses the concept of "intelligent agent" to represent a class of the autonomous intelligent agents (like computer and software) that are able to pursue goals, perceive their environment, react on the environment, learn from other agents, and update its knowledge base. (Mills and Stufflebeam, n.d.)

There hasn't been a uniform definition of the IA concept and researchers haven't reached a consensus about its values in practical applications. In order to get enough related and useful articles, the literature search uses more than one query. Table 1 shows the search query as entered in the website of *Scopus.Com* in November, 2015 and the search results of each query. The asterisk sign (*) helps to include all results for multiple worlds defining the same or similar words. So the search term '*man', includes both 'man' and 'human', and the search term 'augment*' includes 'augment', 'augmenting' and 'augmented'.

As the concept of 'machine' is wide range, the search limits the subject areas to narrow down the number of research results:

The subject areas are limited to 'computer science', 'social science', 'decision science', and 'business management and accounting'.

Table 1 Search query

Search query	**Search results**
TITLE-ABS-KEY("intelligence amplification")	14
TITLE-ABS-KEY ("amplified intelligence")	5
TITLE-ABS-KEY ("intelligence augmentation")	20
TITLE-ABS-KEY ("augment* intelligence")	15
TITLE-ABS-KEY ("*man computer symbiosis")	29
TITLE-ABS-KEY ("*man machine symbiosis")	39
TITLE-ABS-KEY ("*man machine collaboration") AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "BUSI"))	79
TITLE-ABS-KEY ("*man computer collaboration")	73
TITLE-ABS-KEY ("*man computer cooperation")	69
TITLE-ABS-KEY ("*man machine cooperation") AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "BUSI"))	150
Summary	493

The initial search resulted in 493 results. Figure 1 illustrates the selection process of the relevant articles. In the first phase, articles were selected by the relevance of the title. In the second phase, articles were selected based on the abstract. Then, this thesis filtered out the articles that aren't accessed to retrieve the full text. The final papers were selected according to the relevance of the content.

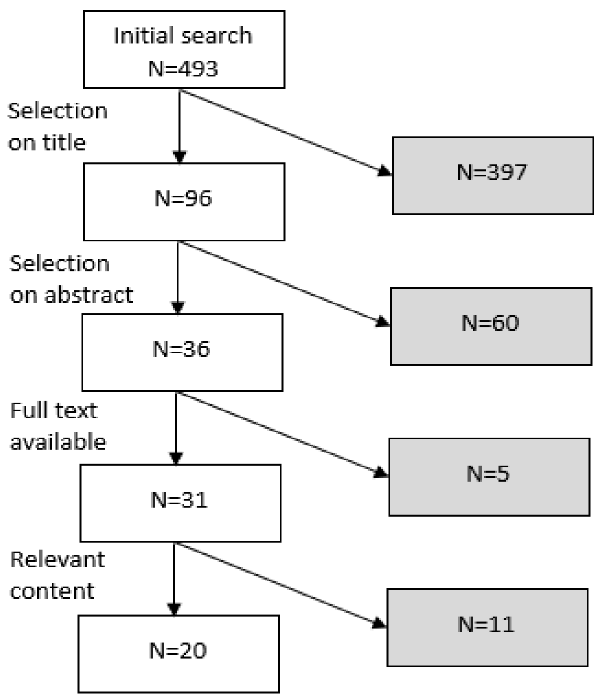


Figure 1 IA Literature selection process

Table 2 provides the overview about which literature addresses which knowledge questions.

Table 2 IA literature review

		Role of human	Relationship between humans and intelligent agents	The application of IA and the benefits	Framework / framework
1	Ahmed and Hasan, 2014		p321	p320-325	p322
2	Arsene et al.,2015		p1827		p1827-P1833
3	Brangier and Adele, 2011		p14-15 & p20		
4	Casini et al., 2015	p200 & p205	p200-201		p200-202
5	Garcia, 2010	p338	p338-339		p339-344
6	Cummings, 2014		p62-68		p63-68
7	Griffith and Greitzer, 2007	p42	p43-49	p43	
8	Jacucci et al., 2014		p5-13		p11-13
9	Kondo et al., 2010	p471-474	p472-474	p471 & p482	p474-p479
10	Lange et al., 2014		p97-98		
11	Lesh et al., 2004		p1290-1294		
12	Ramchurn et al., 2015		p8 & p22-23	p1-4	
13	Reda et al, 2013			P1-6	p4-6
14	Roy, 2004		p121-122	p123	
15	Stumpf et al., 2009	p1-2			p22
16	Sun and Cai, 2011			p1	
17	Tan et al., 2009		p152 & p154		p153-155
18	Williams et al., 2014	p4690	p4690-4692	p4695	
19	Woolley and Stanley, 2014	p1 & p3		p1 & p8	
20	Xia and Maes, 2013		p2	p2-5	p2-3

2.1.2. IA: the role of human in the IA system

Griffith and Greitzer (2007) contend that humans should be in the superordinate position to overcome the limitations of computers. For example, in the object recognition, the automated target recognition algorithms suffer from excessive false alarm rates and have an inability to adapt to different environmental conditions (Williams et al., 2014). Kondo et al. (2010) suggest to have the presence of a user in the object recognition system, particularly when there are dynamic changes affecting the target recognition. Humans' flexibility and cognitive abilities can simplify recognition tasks and increase the accuracy of the object recognition. Besides, in the process of acquiring knowledge to accomplish tasks, the automatic knowledge acquisition methods do not always work well because knowledge keeps evolving with time and is fragmented and scattered throughout many resources. Garcia (2010) addresses this limitation by involving humans in the knowledge acquisition process to use humans' collective knowledge.

The fully automated processing without humans' intervention is error prone (Casini et al., 2015). In Casini et al (2015) research, humans' involvement dramatically increased the system's accuracy by preventing the error propagation. The results of Stumpf et al (2009) study also indicate the benefits of humans working hand-in-hand with intelligent agents. Woolley and Stanley (2014) demonstrate that humans' insights significantly reduce problem's complexity and enable to find solutions faster than the fully-automated process.

In general, the above researches mention the benefits of involving humans in resolving complex and dynamic problems, in comparison to the full automation. But, the aim of these researches to involve humans is to help overcome the limitations of automation. They didn't pay attention to how humans' capabilities are influenced. Concerning the IA concept, this thesis, not only requires humans' involvement but more importantly highlights the human's central role in solving problems.

2.1.3. IA: the relationship between humans and intelligent agents

Licklider's vision of IA is the man-computer symbiosis. Brangier and Adele (2011) identify four types of the human-technology symbiosis: *Co-extension, Co-evolution, Co-action, and Co-dependence*. They regard symbiosis as an interdependent relationship between two entities that both benefit from cohabitation. They further present technosymbiosis to describe the relationship that technologies assist the involved human to improve the degree of efficiency and quality. Xia and Maes (2013) believe that the system and the user can learn from each other to achieve co-evolution. Griffith and Greitzer (2007) view the symbiosis as the symbiotic interaction between humans and the information. Jacucci et al. (2014) summarize the interdependence between humans and machines as: *telepresence, affective computing, persuasive technology, mixed initiative interaction, and symbiosis*. Symbiosis magnifies human abilities through the reciprocity of computer and humans.

There are also researches discussing the relationship between humans and intelligent agents in terms of different tasks.

Ahmed and Hasan (2014) implement the "Human – Agent Teamwork" concept in their detection system where humans supervise the autonomous agent. If the user is unable or not interested to control the agent, the agent has ability to take decisions based on predefined rules and priorities. If the decision made by the agent does not satisfy the user, the user can make changes to minimize the error rate. For Kondo et al. (2010), the relationship between the user and the recognition system is collaborative and mutually beneficial. The recognition system provides the user with his/her expected supports and in return, the function of recognition system is enhanced by the user's involvement. Tan et al. (2009) classify the human-machine cooperation into four types: *independent operation, synchronized cooperation, simultaneous cooperation, and assisted cooperation*.

According to Garcia (2010), the intelligent agents provide useful complement to humans' problem solving abilities by expanding their knowledge base. Williams et al. (2014) also hold a complementary viewpoint to cooperatively fuse the efforts of humans and computers. The ways they introduce to leverage humans and automated algorithms for improving object recognition are: *1. humans aid automated algorithms via the active feedbacks; 2. automated algorithms aid humans through saving resources (time and human effort), offering the rough estimates and providing the complementary information*. The automated algorithms benefit humans in the aspects where humans are perceptually limited (Williams et al., 2014). Casini et al (2015) develop a similar form of humans' intervention in an asynchronous way: a) systems ask feedbacks from the operator; b) the random inspection by the operator; c) the operator chooses to inspect drill-down. Both the human operator and machines mutually provide active assistances in a close and continuous interaction to improve the entire system's performance (Casini et al., 2015).

Based on the above literature review, the relationship of humans and intelligent agents in the IA system can be summarized as collaborative, interdependent, mutually beneficial and complementary. Table 3 reflects the results of the literature review concerning the relationship.

Table 3 Literature results of the IA relationship between humans and intelligent agents

	Collaborative	**Interdependent**	**Mutually Beneficial**	**Complementary**
Brangier and Adele (2011)		✓		
Xia and Maes (2013)				✓
Griffith and Greitzer (2007)			✓	✓
Jacucci et al. (2014)	✓	✓	✓	
Ahmed and Hasan (2014)	✓			✓
Kondo et al. (2010)	✓		✓	
Garcia (2010)				✓
Williams et al. (2014)			✓	✓
Casini et al (2015)	✓			✓

In Table 3, most of researches mention that humans and intelligent agents complement each other in the IA system. That is, IA combines the strengths of humans and intelligent agents to overcome their respective limitations through the collaborative effort.

Humans and intelligent agents both have their own strengths and weaknesses. From the literature review, Table 4 compares the strengths and limitations of humans and intelligent agents in the main attributes of solving a problem.

Table 4 The strengths and limitations of humans and intelligent agents

Attributes	Human	Intelligent agents
Speed (Cummings, 2014) (Casini et al., 2015)	Comparatively slow	Superior
Calculation accuracy (Cummings, 2014) (Casini et al., 2015)	Comparatively weak	Superior
Information capacity & Memory (Cummings, 2014) (Griffith and Greitzer 2007) (Garcia, 2010)	Limited in single channel to gain information. Good at making principles and strategies	Superior in searching, retrieving, processing and integrating large volumes of data from multichannel, and tracking & updating status of tasks
Reasoning (Cummings, 2014) (Griffith and Greitzer 2007)	Inductive & Deductive reasoning	Deductive reasoning
Handling uncertainty (Griffith and Greitzer 2007)	Superior in anomaly detection / recognition and adaptability to change	Weak, depends on formal and restricted pre-program setting.
Analysis (Cummings, 2014) (Griffith and Greitzer 2007) (Casini et al., 2015)	Better at judgement, problem identification, contextual evaluation, pattern recognition, nuanced assessment	Good at the quantitative assessment and results presentation
Creativity (Griffith and Greitzer 2007)	Superior in innovation and creative insights	Comparatively weak, good at advising on alternatives

The collaboration of human – agent combines humans' flexibility and intelligent agents' efficiency to address the complex requirements (Tan et al., 2009). Intelligent agents perform efficiently in identifying task status, suggesting alternatives, monitoring, processing information, and testing hypotheses (Griffith and Greitzer, 2007). Humans' performance will be augmented through these effective functions without losing control, which attributes to the intelligent agent's ability to implicitly detect the human goals. In decision making process, Garcia (2010) explains that autonomous agents are important in dealing with tremendous amounts of information, systematically exploring a variety ranges of alternative choices, checking the decision's consistency with norms, and detecting changes. While, humans play a fundamental role to creatively think of solutions and visually perceive patterns. Levels of automation help to understand how humans can interact with a complex system in decision making (Cummings, 2014) (Roy, 2004).

However, instead of thinking about which tasks are performed by humans and which by automation, Casini et al. (2015) suggest to think about how tasks can be best shared by humans and intelligent agents working cooperatively, and how competencies of humans and intelligent agents can be enhanced through an appropriate form of mutual interaction. When there is a risk of overload, humans should know clearly and concentrate on the most critical tasks that they are superior to automation in addressing, while the automation takes charge of making other less "human-critical" decisions (Lange et al., 2014).

Hereby, in order to achieve IA, the right human-intelligent agent collaboration, it is necessary to study on human-intelligent agent function allocation in the IA system, according to the nature of specific tasks. In other words, there is a need to find ways to solve the task assignment when implementing IA into problem resolution.

2.1.4. IA: what IA is used for, and what benefits can it bring to

There are researches using the "human-computer collaboration" concept to address complicated tasks successfully.

Williams et al. (2014) present strategies to cooperatively employ the skills of human operators and the automated computer algorithms in the task of underwater object recognition. From the experimental results of a real mine search, they demonstrate that fusing the skills of humans and computers significantly improves the performance which is beyond when humans and computers working alone, due to diversity of views and available complementary information. Kondo et al. (2010) also introduce the "human-computer collaboration" concept to improve the accuracy of object recognition.

In the medical area, Arsene et al. (2015) use the idea of collaborating specialists with software to achieve the knowledge sharing among all specialists and to increase the diagnosis accuracy. Garcia (2010) also suggests to apply IA in the fault diagnosis. In the study of Ahmed and Hasan (2014), the teamwork of an agent and a human gives a better performance to detect the cancer. Their results show that the early detection of breast cancer becomes fruitful and effective, and the decisions become more accurate because of humans' creativity and the agent's intelligent.

Reda et al. (2013) adopt a human-computer collaborative analysis that lets a human analyst and a computer to work together to accurately identify the movement of terrestrial insects. The computer semi-automatically processes the video visual segment and tracks insects, while the human analyst makes judgements, interprets insects' behaviors, and gives corrective interventions in an ambiguous situation to improve the tracking precision.

Garcia (2010) and Ramchurn et al. (2015) evaluate the human-agent collaboration in an uncertain environment, the dynamic disaster response. Their results present that the planning agent augments humans' performance by providing useful instructions and taking into account the human capabilities and preferences. In the process of path planning, Sun and Cai (2011) integrate humans' perception, knowledge and experience with the computer's power and accuracy of computing to reduce the complexity of reality conditions and meet the real-time requirements.

The examples showed in literature take advantage of the collaboration of humans and computers, but don't realize this benefit belongs to the IA concept. And most focus on the improvement of the entire system's performance in completing tasks, without specifically studying the amplification effects of humans' intelligence. As concluded in Section 2.1.2, humans play a crucial role in IA system, thus there is a need to study whether humans' activities and capabilities are amplified by IA.

From literature, we can indicate that IA not only helps to improve the entire system's performance of completing tasks, but also magnifies humans' performance along various cognitive and physical dimensions (Roy, 2004). The Media Lab introduces the potential '10x' human performance, for instances: *extend human's physical abilities*; *access to large stores of memory to expand human's cognitive abilities*; *augment human expression*; *enable people to view and understand situations in new ways*; *extend human awareness to the events that are not detectable by the unaided human senses and that are not in a person's immediate physical environment.* Griffith and Greitzer (2007) conclude that IA can be used to increase humans' understanding of problems from a variety of contexts, and form more creative insights by the support of computers.

For Garcia (2010), IA amplifies humans' capability of making better decisions in choosing alternatives of goal oriented tasks. Humans benefit greatly from the knowledge manipulation and extraction as well as from the systematic examination of the ranges of alternatives. Jacucci et al. (2014) believe that the collective symbiotic system is a prospective theme. Amplifying humans' capabilities of searching can be achieved not only by chaining users to accumulate all the users' knowledge and discoveries, but also by combining a human with the automated search (Woolley and Stanley, 2014). In Woolley and Stanley's approach, the rate and quality of searching is accelerated by leveraging humans' knowledge without burdening the user with the responsibility of evaluating all the candidates, much of which was automated by the novelty search.

As mentioned in Section 2.1.3, IA is a mutual beneficial relationship that both humans and intelligent agents can benefit from. Table 5 depicts examples of IA's mutual benefits and applications in the literature.

Table 5 Examples of IA's benefits and applications

Benefits	**Beneficiary**	**Examples of application**
Increase understanding of the problem context, and simplify the complexity of reality conditions	Intelligent agents; Humans	Path planning
Improve the accuracy of recognition, detection and tracking	Intelligent agents; Humans	Object recognition Cancer detection (Insects / animals) Movement pattern identification
Gather data from multiple sources; acquire more valuable knowledge; generate more effective solutions	Intelligent agents; Humans	Diagnosis Collective intelligence
Increase the awareness of uncertainties; better deal with the uncertain and dynamic conditions	Intelligent agents; Humans	Disaster response
Better decision making; support judgements with better reasoning	Humans	Choosing alternative in goal-oriented tasks
More creative insights with the expanded cognitive activities	Humans	Pattern recognition Accidents investigation

All the above examples in literature share some common attributes that give us insights about what kind of task or problem is more suitable to introduce the IA concept. Figure 2 displays three common attributes of an IA problem.

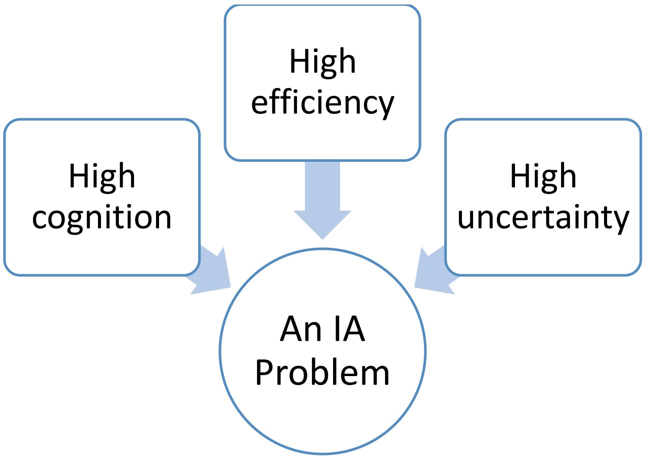


Figure 2 Attributes of an IA problem

1. High need of humans' cognitive capability

When the problem or situation is vague and ambiguous, humans' interpretation, judgement and corrective intervention are critical to understand problem and recognize the goal of resolution. Especially, when the problem is unique and needs to consider multiple factors or criteria at the same time, a nature of an IA problem has been found that multiple objectives cannot easily be combined into one single objective (Riddell and Wallace, 2011). Due to the lack of the understanding of problem context, the complete automation is faced with the risk of acquiring inappropriate knowledge, conducting wrong procedures and pursuing wrong goals. In this case, humans play a crucial role in reducing problem's complexity and defining goals by their cognitive capabilities. Besides, humans can direct and supervise intelligent agents, as a guide, to find solutions faster and effectively accomplish tasks. Moreover, humans can pour their innovative and creative insights to achieve an optimal solution.

2. High requirement of efficiency

Most of complex tasks need to integrate vast volumes of heterogeneous data to generate more alternatives for an optimized solution, which requires computer aided resolution. As illustrated in Table 4, intelligent agents are superior in processing large volumes and variety of data in terms of speed, information capacity and memory. Besides, in most of time, the problem with many variables and constraints requires to be solved within the limited amount of time. Automation can address the routine work with complex requirements by its efficient functions to save time and efforts. Hence, humans need the intelligent agent, as an assistant, to fulfill tasks efficiently and effectively.

3. High degree of uncertainty

There is a highly frequent occurrence of uncertainties or unexpected circumstances. Coping with uncertainties needs real-time adjustments to the dynamic changes of environmental conditions and affecting variables. It is known that automation is inherently brittle in unanticipated events because automation can only account for the quantifiable variables identified beforehand. In the contrary, humans are superior in making intuitive decisions by detecting and assessing both quantifiable and qualitative information. Humans' flexibility and cognitive abilities can simplify the complexity of problem and enable to make a rapid response to unforeseen and uncertain situations. Thus, under a high uncertain circumstance, the decision-making loop needs humans to provide flexibility and creativity in problem solving.

In a word, when it is necessary to combine automation's efficiency with humans' flexibility and originality to address complex, ambiguous and uncertain problems in real time, it may be a potential area that IA can contribute to.

2.1.5. IA: framework / framework mentioned for application

There are some studies explaining their ways of introducing the human-machine collaboration to solve practical problems. Kondo et al. (2010) propose a loop-back framework of collaborative recognition by using user's feedback to improve unfavorable situations. Ahmed and Hasan (2014) build an agent learning mechanism to include humans' inputs through a human-agent teamwork. Tan et al. (2009) believe that the task frame working approach is a good way to enhance the human-machine collaboration through defining goals, roles, and task activities. Reda et al. (2013) present a human-computer collaborative workflow with a human-guided video processing method to acquire and analyze insects' behaviors.

There are also some researches discussing the requirements of a good human-intelligent agent collaboration. Casini et al. (2015) regard *observability & directability and predictability & learning* as the bases of a successful and resilient human-machine teamwork. The observability enhances humans' ability to understand and evaluate the situation, while the directability helps humans to implement their goals. Stumpf et al. (2009) conclude three components of humans' interaction in an intelligent system: *1) the intelligent system should explain its reasoning to humans, 2) humans should reason their adjustments and critiques, 3) make use of humans' feedbacks to benefit the system and ultimately benefit the human*. Lesh et al. (2004) argue that the true symbiosis requires to achieve three elements: *a complementary and effective division of labor between human and computer; an explicit representation in the computer of the user's abilities, intentions, and beliefs; and the utilization of nonverbal communication modalities*.

Most of above studies involve humans' tacit knowledge by making using of humans' inputs or feedback as a way to achieve the collaboration of humans and intelligent agents in solving problems. Only Garcia (2010) presents the AGUIA (Agents' Guidance for human Intelligence Amplification) framework for IA. The AGUIA has two basic constructs: 1) the agents that use knowledge to enhance users' understanding of problems and help users explore alternatives to find a better solution; and 2) the agents that collect knowledge in the context of the problem resolution for updating the knowledge base. Therefore, there is a lack of applicable framework for implementing IA.

The problem solving is comprised of numerous processes in the form of process hierarchy (Xia and Maes, 2013). Xia and Maes (2013) argue that IA augments the system as a whole, instead that only humans gain benefits. They suggest to consider the desired state of humans' intellect that is planned to be amplified through the process analysis, and to explore what kind of intelligent agents we can introduce to simplify processes. IA emphasizes the importance of humans' involvement, but, it doesn't mean that IA only amplifies humans' intelligence. Rather, both humans and intelligent agents mutually benefit from the IA system. This collaborative and complementary human-intelligent agent relationship will in the end augment the entire system's performance of problem solving. Hereby, this thesis concludes that it is a good way to start analyzing and framing the whole aggregated process of completing tasks instead of only focusing on one entity's improvements, either humans or intelligent agents.

On the other hand, we still need to be aware of the potential challenges of implementing IA. The challenges and effects can be: 1) the adversarial effects caused by humans' intervention (Casini et al., 2015) (Xia and Maes, 2013), 2) the increasing burden of humans (Williams et al., 2014), 3) the inappropriate interaction design (Ramchurn et al., 2015) (Roy, 2004), 4) the complexity of humans' nature (Tan et al., 2009), 5) humans' biased reasoning (Garcia, 2010), 6) humans becoming dependent on intelligent agents (Xia and Maes, 2013) and 7) ethical questions (Xia and Maes, 2013).

The design process for implementing IA either starts with a human approach that improves humans' performance with the decision support technologies, or starts with an automated approach that enhances automation results with humans' inputs (Casini et al., 2015). To develop an IA system that integrates humans and intelligent agents, we should first analyze the entire system as a whole and then answer the questions about where, when and which level that humans and automation should be in the decision-making loop (Cummings, 2014). Defining roles and assigning tasks of humans and intelligent agents are critical in successfully designing an effective collaboration architecture. The design process will be further introduced in Section 3.

2.2. Decision making: a literature review

In this section, the concept of decision making is investigated. After the overview of search and selection processes, the concept of decision making process is discussed. Then the methods and tools used in decision making are introduced. In the end, this thesis explores whether IA is valuable to be applied in decision making.

2.2.1. Literature search and selection process

The below knowledge questions need to be answered, in order to gain insights from academic literature.

1. What are the processes of decision making?
2. What methods and tools are used in decision making?
3. Is the IA concept needed in decision making?

This thesis focuses on decision making process, thus the keyword of query is 'decision making process'. The search resulted in 141,530 results. To narrow down the number of search results, the following criteria were used:

1. The research involves the methods or technology to study decision making process
2. Papers are published between 2010-2015
3. Search is limited to subject areas 'computer science', 'decision science', and 'business management and accounting'

The search query as entered in Scopus.com in November, 2015 is:

(TITLE-ABS-KEY (decision making process) AND (TITLE-ABS-KEY (method) OR TITLE-ABS-KEY (technology))) AND PUBYEAR > 2009 AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "DECI"))

After setting criteria constrains, 8,711 results remained which was still a large number. So this thesis filtered articles by citation count. The top 50 cited articles were selected based on the relevance of the title. Next, this thesis selected articles from this 50 subset according to the abstract. Then, this thesis filtered out unavailable articles. In the end, 16 articles were selected in terms of the relevance of the full content. Figure 3 presents the selection process.

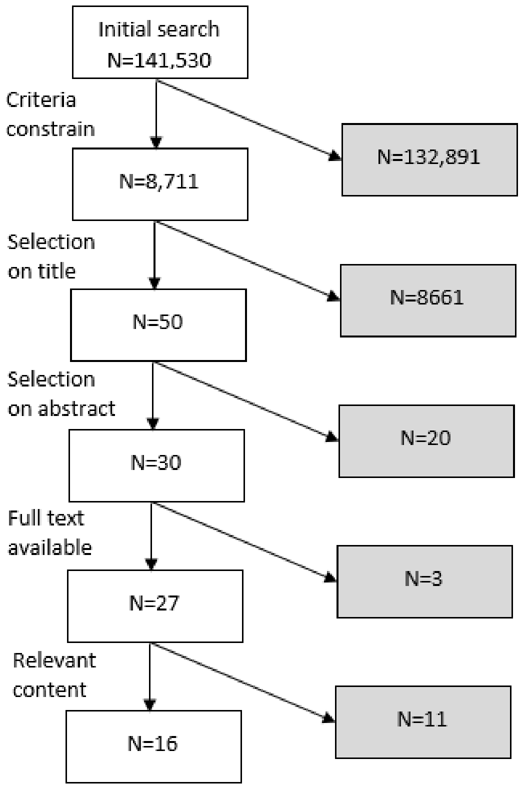


Figure 3 Decision making literature selection process

During the review process, I also used the *Backwards Search* in order to gain sufficient knowledge on the studied literature. Table 6 provides an overview on which articles give an answer to which search questions. There are two articles that indirectly address the research questions, thus, Table 6 shows 14 articles instead of 16.

Table 6 Decision making literature review

		Decision making process	Method/tool	IA in decision making
1	Akhouayri et al., 2012		p167 & p171	
2	Andrade et al., 2006		p179-180	p179
3	Antunes et al., 2014	p276	p272	
4	Draghici et al., 2013	p65		
5	Elmegreen et al., 2014	p944	p945	p944 & p948
6	Guillemette et al., 2014	p619	p618	
7	Moreno-Jiménez et al., 2012	p1922	p1923	p1921
8	Negoita et al., 2013	p4-5		
9	Nutt, 2008	p425-427 & p446-447		
10	Pkirs.utep.edu, 2007	P1		
11	Roberto, 2004	p625-628, p639 & p653		
12	Saaty, 2008		p85	
13	Umassd.edu, 2015	p1		
14	Zhong et al., 2016		p85-87	p87

2.2.2. Decision making: decision making process

Decision making means taking actions to make choices that produce outcomes with the immediate and downstream effects (Nutt, 2008). Decision makers make decisions by following the process that consists of tactical steps. These steps facilitate individuals to find out what to do and to reason their actions. The efficient decision making means that the process executes smoothly and decision makers select a course of actions in a timely manner. The effective decision making is that the selected course of actions meet the objectives established during the decision process (Roberto, 2004). The key factors influencing decision making have been: *the context of decision making environment, the content of decision, the action-taking procedures to make a decision, and the relationships among the previous factors* (Nutt, 2008). Negoita et al. (2013) also conclude the factors shaped decision making which are *the nature of issue, solution types, politics, and individual factors*.

The quality of a decision depends on the performance of decision making process that offers insights into the sequence and nature of actions about how to make a decision (Guillemette et al., 2014). Simon develops a three-stage framework of decision making: *intelligence, design, and choice* (Pkirs.utep.edu, 2007). The *intelligence phase* identifies the problem and gathers information concerning the problem. The *design phase* develops possible solutions for the problem. Finally, the *choice phase* evaluates all alternatives and selects a final solution. Some researchers studied decision making based on Simon's framework. Guillemette et al. (2014) evaluate the performance of decision making process based on Simon's framework. Antunes et al. (2014) extend the Simon's framework to four phases: *Intelligence, Design, Choice and Implementation & Evaluation*. Negoita et al. (2013) also identify decision making process into three phases. They explain that the decision process begins with the *identification phase* when the key objectives and direction are identified. Then the *development phase* follows to analyze related solutions. Through evaluating the criteria and priorities, during the *selection phase*, decision makers select the best alternative solution. Elmegreen et al. (2014) present decision making in three steps too: 1) acquire information about the consequences of possible actions, 2) evaluate alternative actions with defined weights, and 3) make judgements about choosing which action.

Some researchers define decision making process in more detail. In Nutt's (2008) research, the steps of decision making are: *intelligent gathering, direction setting, option development, evaluation, and reactive implementation*. The ELECTRE method proposed by Draghici et al. (2013) defines the main decision making process as: *problem statement, decision criteria hierarchy establishment, mathematical framework definition, optimal solution result, and optimal solution implementation*. According to Umassd.edu (2015), decision making is the process of selecting alternatives by setting goals, collecting information, and assessing alternative values. There are seven steps to make an effective decision: *1. Identify the decision, 2. Gather relevant information, 3. Identify alternatives, 4. Weight evidence, 5. Choose among alternatives, 6. Take action, 7. Review decision and consequences*.

Based on the above literature review, the decision making process in this thesis consists of four phases: 1. Decision Identification phase, 2. Solutions Identification phase, 3. Selection phase, and 4. Implementation & Evaluation phase (see Figure 4). The Decision Identification phase recognizes the context of making a decision and gathers information related to the decision. The Solutions Identification phase generates possible solutions for the problem.

Then, the Selection phase follows to assess all alternatives and select a final solution. Finally, the selected solution need to be implemented in the Implementation & Evaluation phase so that we can evaluate the results of implementation and further decide whether to redevelop or make a new decision.

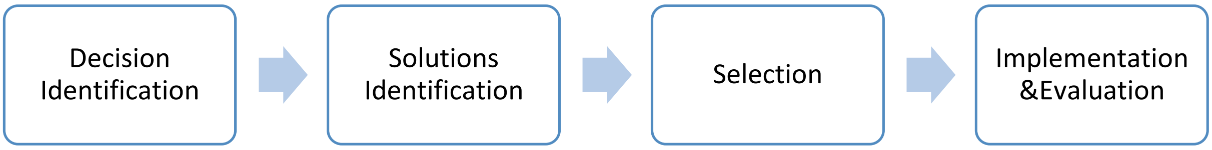


Figure 4 Decision making process

2.2.3. Decision making: methods or tools are used in decision making

Two methods are often employed in decision making for selecting an appropriate resolution of complex problems.

The analytic hierarchy process (AHP) is an extensively used multi-criteria decision making (MCDM) approach (Moreno-Jiménez, 2012). AHP is a theory that measures pairwise comparisons and relies on the judgements of experts to determine the priority scales. AHP analyzes the problem within a hierarchy structure of decision making process, from the top (objectives) through the intermediate level (criteria and sub-criteria), and on to the lowest level (alternatives). With the AHP method, the decision is made in four steps: *1. Define the problem and information collection, 2. Structure the decision hierarchy, 3. Construct a set of pairwise comparison matrices, 4. Weigh the priorities.* (Saaty, 2008)

Another method is the Fuzzy logic theory. Fuzzy logic deals with the reasoning of partial truth where the truth value ranges between completely true and completely false (Akhouayri, 2012). According to Andrade et al (2006), Fuzzy logic is a convenient approach for decision making as this method incorporates linguistic statements into formal frameworking. Hence, the expert opinions and subjective information can be combined with the theoretical knowledge by Fuzzy logic, which ensures a rational decision making when handling complex and dynamic problems. The Fuzzy rule to classify inputs is based on IF-THEN rule:

IF variable IS adjective THEN class

Information technology (IT) has been applied as a useful tool to support decision making (Guillemette et al., 2014). For examples, Visual analytics tools support decisions by boosting humans better insights (Zhong et al., 2016), ERP Systems provide individual workers with great supports in evaluating alternatives (Guillemette et al., 2014), Executive Information System plays an important role in gathering data for decision making (Guillemette et al., 2014), as well as the various decision making support systems (DSS) etc. During decision making process, we need information to guide our decisions and actions towards the desired goal. Antunes (2014) explains how DSS supports decision making through processing and sharing information: *(1) information extraction and selection; (2) information integration; (3) information extension, exploration and explanation; (4) information interpretation, event detection, and prediction; (5) information tracking and post-event analysis; (6) frameworks presentation; (7) sharing decisions*. Elmegreen et al. (2014) demonstrate that the computer simulation supports decision making by rapidly creating, merging, searching, displaying and analyzing data from various resources. Zhong et al. (2016) mention that the visual technologies help decision making by *(1) synthesizing information and deriving insights from massive, dynamic, ambiguous and conflicting data; (2) detecting the expected and discovering the unexpected; (3) providing timely, defensible and understandable assessments; and (4) effectively communicating assessment for actions*.

In conclusion, the AHP method and the Fuzzy logic theory assist decision makers in the Selection phase to make a choice among alternatives. The IT tools support decision making mainly through extracting, diffusing, and visualizing relevant knowledge of the problem resolutions to decision makers. On the other hand, the effective supports provided by IT tools also indicate the benefits to involve intelligent agent(s) into decision making.

2.2.4. Decision making: the IA concept in decision making

As one of humans' fundamental cognitive characteristics, decision making emphasizes the human's vital role in decision making process (Moreno-Jiménez et al., 2012). Moreno-Jiménez et al. (2012) highlight the importance of human factors in acquiring knowledge during decision making, such as humans' education and their continuous learning abilities. Zhong et al. (2016) mention that the tacit knowledge is essential to create insights of an optimal decision. The tacit knowledge is derived from personal experiences which is difficult to be codified into a program. Andrade et al. (2006) also state that embodying humans' tacit knowledge and reasoning into decision making improves the business intelligence and helps achieve the strategic goals more effectively. Hereby, this thesis can state that there is a need to take into account humans' tacit knowledge, mental capabilities and creativity in decision making process.

Section 2.2.3 indicates the benefits of IT tools' support in assisting decision makers to achieve efficient operations, such as information searching, scenario analyses, and hypothesis testing. Particularly when the decision requires to be made within limited time and there is a need to handle unstructured and enormous amounts of data from various sources, intelligent agents can efficiently and effectively aid humans to make a decision in a short time.

Each step of decision making is a challenging task for either humans or machines to successfully and smoothly complete, for instance, the task of weighing alternatives (Elmegreen et al., 2014). The complexity of business problems in reality increases the difficulty to make a proper and right decision due to real-time requirements, the uniqueness of problem, lack of relevant information, diverse goals, various stakeholders as well as the high occurrence rate of uncertainties. Elmegreen et al. (2014) argue that it is inability to make a single best decision by either a human or a computer. Humans may disagree or be confused with the outcomes that are automatically made by automation. They suggest that computers aid humans in decision making by providing humans with more valuable information to augment their existing knowledge, and humans are involved in the decision making loop considering the broad context and making the final decision.

Thereby, from the above literature review, the necessity of collaborating humans with intelligent agents to make better decisions can be easily identified. In other words, the findings from literature indicate that decision making is a potential research area to study IA's application.

On the other hand, with respect to the amplification of human intelligence, except the problem solving ability, humans can also benefit much from the augmentation of cognitive aspects, such as decision making, memory, motivation and mood (Xia and Maes, 2013). But, the IA research on humans' cognitive activity tends to be more oriented towards attention and perception process, and less towards decision making and thinking (Griffith and Greitzer, 2007). Hereby, the research value of this thesis is to prove IA's practical value in decision making.

2.3. Conclusion

This thesis aims to evaluate IA's benefits and values in practical application. In IA system, humans play a central role in problem resolution and IA augments humans' intelligence of solving a problem. Humans, as a guide, direct and supervise intelligent agents, while intelligent agents, as an assistant, aid humans to fulfill tasks efficiently and effectively. IA emphasizes the strengths of humans and intelligent agents to overcome their respective limitations through the collaborative effort. Hereby in IA system, humans and intelligent agents have a collaborative, mutually beneficial and complementary relationship. Due to this relationship, IA improves the entire system's performance of problem solving.

There are many researches taking advantage of the collaborative effort of humans and computers without realizing the IA concept. Besides, most of them focus on the benefits in overcoming the limitation of automation and improving the performance of entire system in completing tasks. Few specifically study IA's amplification effects of humans' intelligence. Thus, the thesis contributes to explore IA's benefits and study whether humans' capabilities and performance are amplified by IA.

In order to evaluate IA's benefits, there is a need to find ways to apply IA in problem solving. Since IA is in its infancy, the current state of art is lack of the applicable framework for implementing IA. This finding indicates the importance of designing an approach on how to accomplish this task. Thus the goal of solution is to develop a framework that provides instructions of IA implementation.

In terms of achieving IA, it is necessary to effectively explore the collaborative effort of utilizing the best of humans and intelligent agents. As IA amplifies the system as a whole, we can firstly think about the desired state of completing tasks, instead of considering humans or intelligent agents separately. Then we analyze and frame the whole aggregated process to meet this desired state. During the process analysis, the task assignment can be settled according to the nature of specific tasks.

To figure out what tasks can be best shared by humans and intelligent agents working cooperatively, three attributes of an IA problem are identified from literature review: high cognition, high efficiency and high uncertainty. Based on these attributes, decision making is identified as a good candidate for IA research. But, the research into the field of IA has less focused on decision making. Considering decision making 's vital role of business, it is valuable to explore how IA influences decision making and whether decision makers can benefit from intelligence amplification of decision making.

3. IA framework

This chapter applies the design science research methodology (DSRM) (Peffers et al., 2007) to develop an IA framework. The design activities are based on the design cycle, namely, problem investigation, treatment design, and treatment validation (Wieringa, 2014). Figure 5 describes the six activities of DSRM in the design cycle.

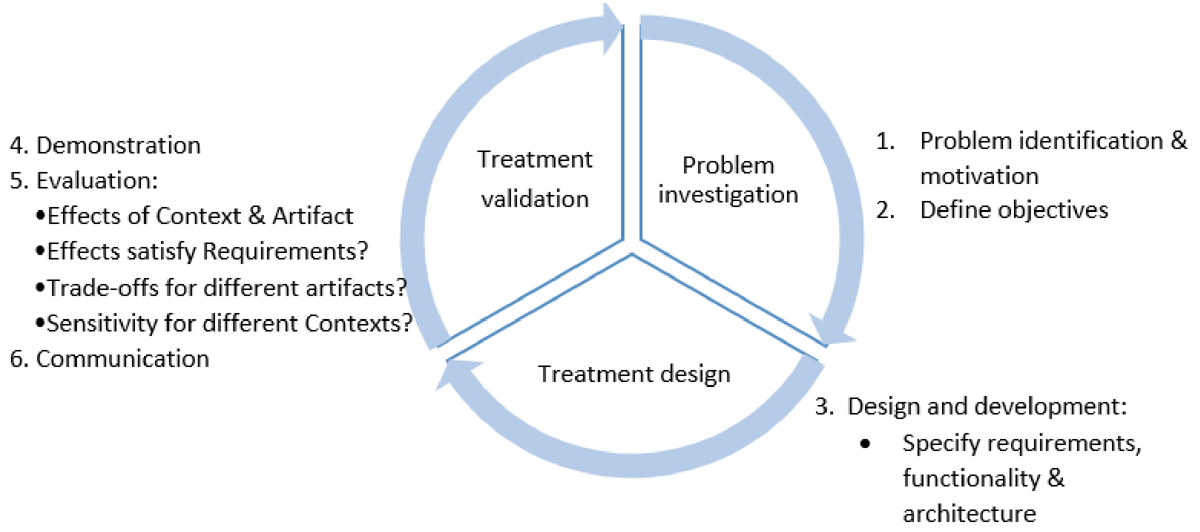


Figure 5 Design Cycle

3.1. Problem identification and Motivation

As discussed in the previous literature review, decision making is a good candidate to study IA's benefits in practical application. However, the research into the field of IA has been less towards decision making. Since there is an increasing desire to have the collaboration of humans and intelligent agents in decision making process, the problem context of this thesis has been chosen in the decision making area. Considering decision making's business value, this thesis explores: 1) how IA influences decision making and 2) whether humans can benefit from the amplification of decision making.

In order to prove IA's value in improving decision making, there is a need to find a way to introduce IA to decision making. Thus the problem of this thesis is about how to apply IA in decision making.

3.2. Objective

The objective of the solution is to develop a framework that gives instructions to apply IA in decision making process. Such a framework should explore the collaborative effort of utilizing the best of humans and intelligent agents, and represent where, when and which level of decision making process that humans and intelligent agents should be in. In other word, the designed framework should solve the task assignment problem. In terms of achieving IA, the framework should also help to decide and design the functionalities of intelligent agents based on the allocated tasks.

3.3. Design and development

The previous literature review identifies that building an IA framework through the process analysis is a good way to introduce IA. Thus this thesis designs a framework that introduces the steps of implementing IA in decision making. Figure 6 presents the framework proposed by this thesis.

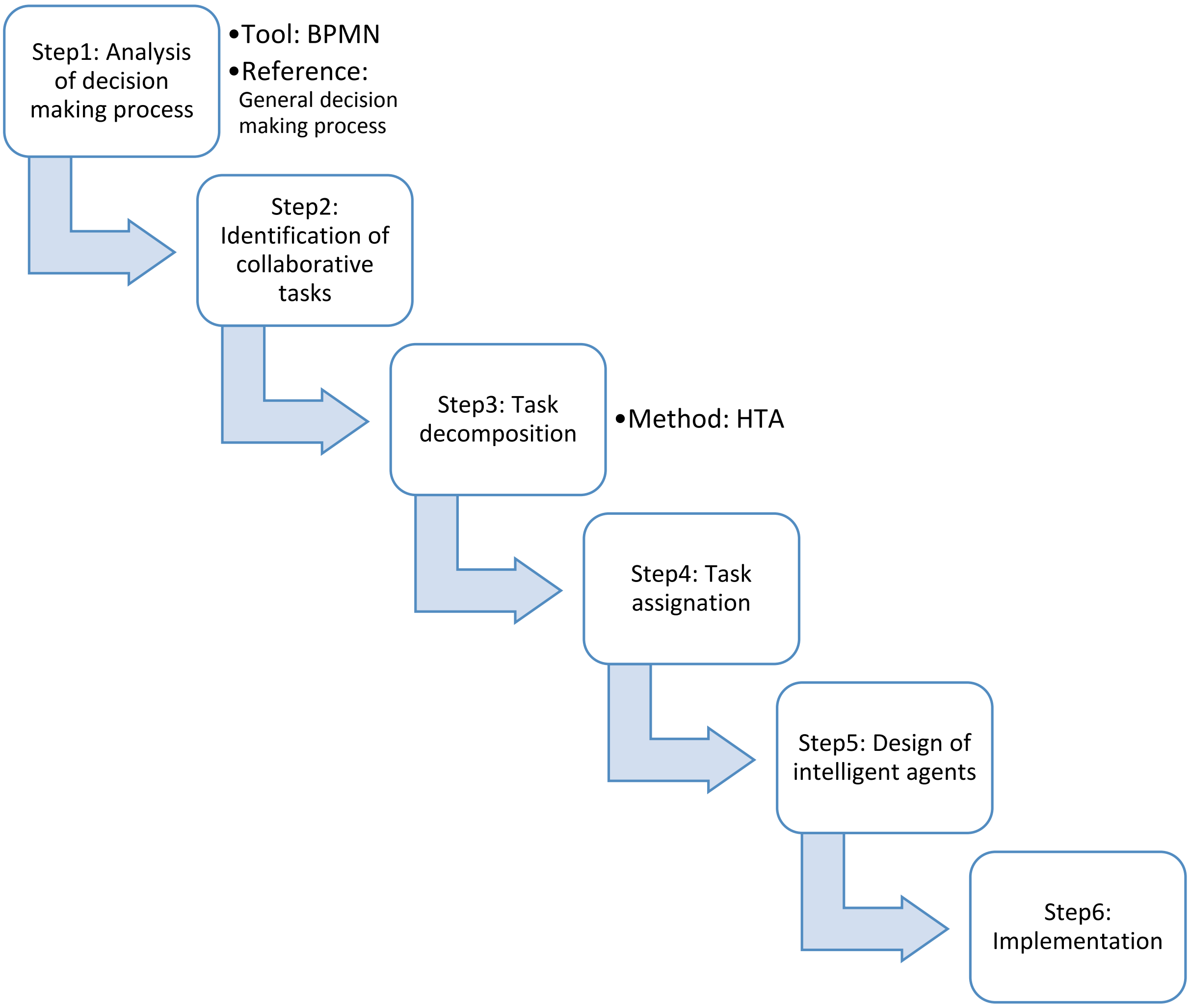


Figure 6 IA Framework

The first step of applying IA is to analyze decision making process based on a specific case. The tool to model decision making process is the Business Process Modeling Notation (BPMN). The general decision making process is explained in Figure 7. Each certain case can base on this general decision making process to build its own specific process. In the first step, the main activities of making a decision can be classified to three types of tasks: automation task, human task as well as the collaborative task on the basis of the nature of tasks. Figure 11 indicates the potential collaborative tasks in the activities of decision making. The collaborative tasks need to be further decomposed to sub tasks that can be assigned to one entity, either humans or intelligent agent. The method of task decomposition is the hierarchical task analysis (HTA). Then, according to the result of task assignment, the functionalities of intelligent agents can be defined. The built intelligent agents are implemented to work with decision makers so that we can evaluate the effects of collaboration.

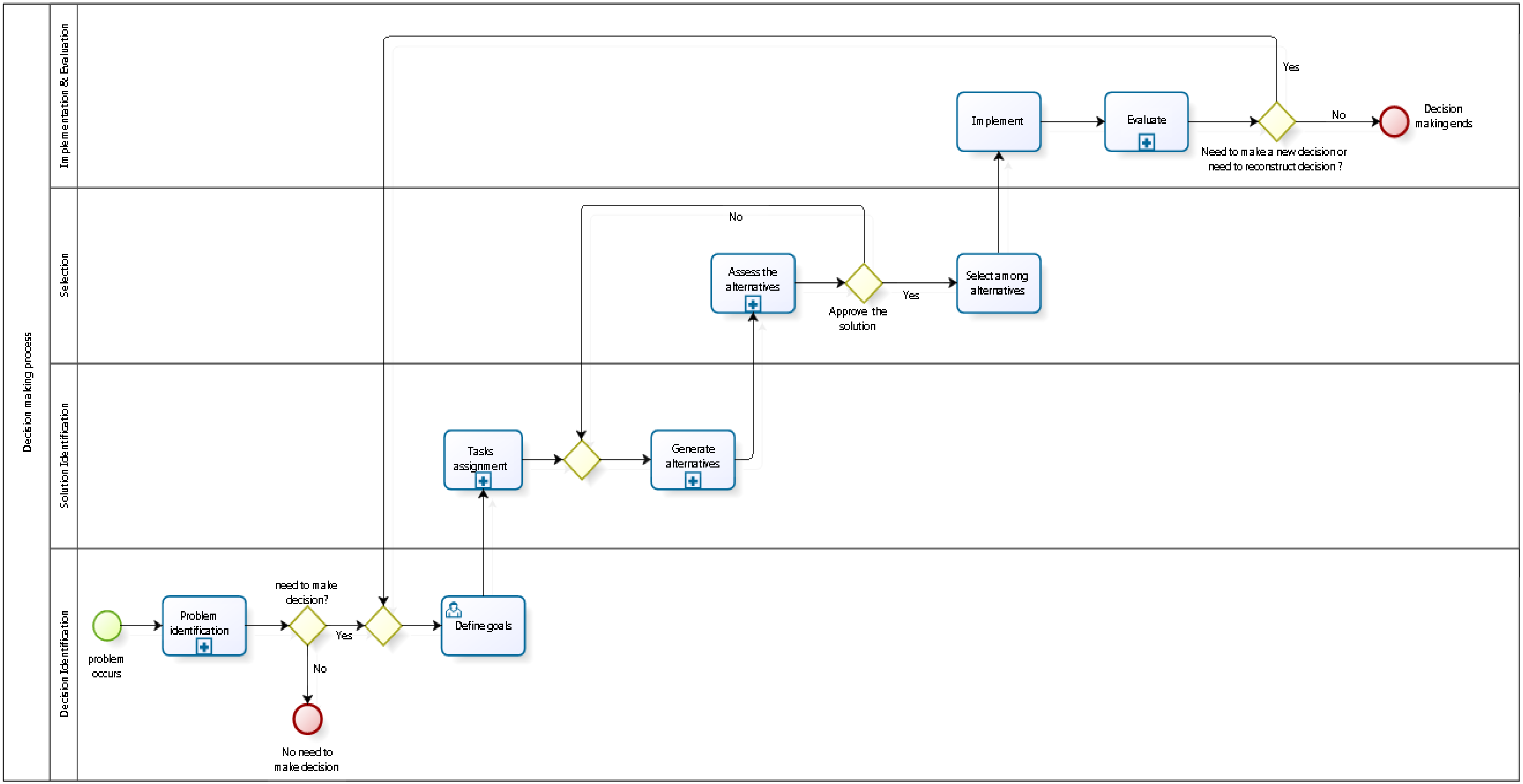


Figure 7 Decision making process

3.3.1. General decision making process

Figure 7 describes the steps of decision making process. This general introduction of each decision making phase helps to better figure out where, when and which level that decision makers and intelligent agents should be in decision making process, and facilitate the understanding of what tasks of decision making should be assigned to humans and intelligent agents.

Knowledge Base

The whole decision making process requires a knowledge base that gathers the needed information to better understand the problem, generate alternatives, select and evaluate the best solution in the given context. The knowledge may be either in the form of explicit knowledge that is available in norms, standards and regulations, or tacit knowledge in the decision maker's minds, experiences and common sense (Garcia, 2010). Moreover, the knowledge evolves with time and circumstances thus it needs to be updated accordingly. According to Table 4, the intelligent agent is superior to humans in handling enormous volumes of heterogeneous information. Along with the ability to learn from other agents, the intelligent agent is able to interact with humans and integrates humans' tacit knowledge to update its knowledge based. As humans are limited in dealing with complex situations due to the difficulties in perceiving context and exploring the range of alternatives, there is a need to have a *knowledge acquisition agent* that elicits knowledge in the context of problem resolutions to augment humans' intelligence during decision making process. Figure 8 explains the process to acquire knowledge.

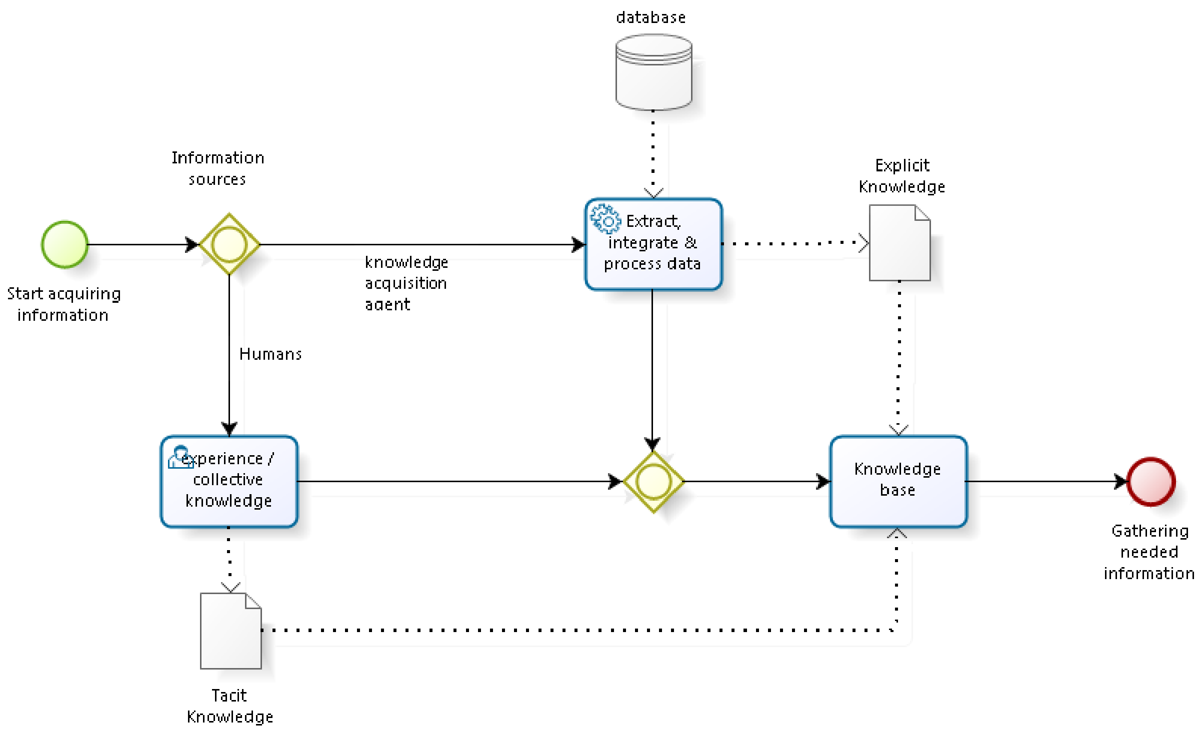


Figure 8 Knowledge acquisition

Decision Identification phase

Decision making process is triggered by the occurrence of problem in the *Decision Identification* phase. The problem should be identified and understood before deciding whether it is an appropriate situation to make a decision. Humans have intrinsic limitations to always keep aware of variants and frequently track updates in a constant changing world. Thus, this thesis lets the intelligent agent to perceive changes and continuously maintain humans' awareness of the problem occurrence. The *knowledge acquisition agent* at that time provides humans with the information related to the problem context in order to help humans better understand the problem and, in the meantime, to avoid humans' misconceptions and biases (Garcia, 2010). Most of times, problems are novel and anomaly that need humans' reasoning to frame the information gathered from the *knowledge acquisition agent* for the sake of a comprehensive and right understanding of the context (See Figure 9). After figuring out the problem, if the decision maker recognizes the need to find a solution of the problem, in the next step, they define the goals of resolution to guide the following generation, selection and evaluation processes. If the decision maker thinks there is no need to make a decision or can wait to consider the problem in the future, then the process comes to an end.

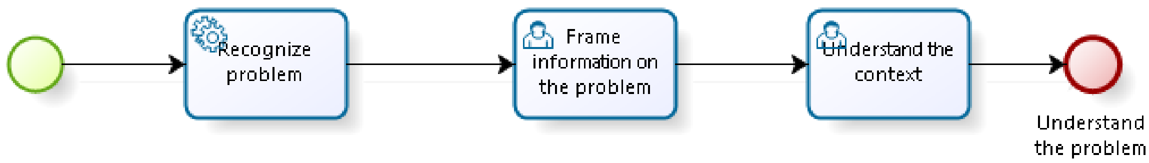


Figure 9 Problem Identification sub-processes

Solution Identification phase

The *Solution Identification* phase starts with assigning tasks to intelligent agents and humans to accomplish the goal defined in the *Decision Identification* phase. Figure 11 reflects that the task assignment is done by an intelligent agent while in the beginning the intelligent agent requires humans to define the rules of task allocation. Task analysis is a scientific approach to framework tasks by defining goals and activities (Tan et al, 2009). This thesis adopts the hierarchical task analysis (HTA) method to decompose the tasks in the generating, selecting and evaluating processes into hierarchies of sub tasks. Table 7 identifies the top level tasks that need to be divided into sub tasks regarding to a specific problem. The further task decomposition will be introduced in the next chapter based on a case study.

Table 7 Top level tasks

Decision making process	**Solution identification phase**	**Selection phase**	**Implementation & evaluation**
Task	1. Generate alternatives	2. Assess alternatives	3. Evaluation

After decomposing the top tasks by HTA, each sub task will be classified to four types: Skill-based, Rule-based, Knowledge-based, and Expertise (Cummings, 2014), so as to facilitate the task allocation to humans and intelligent agents. The process to assign tasks is displayed in Figure 10.

The skill-based task can be accomplished by sensory-motor actions that require very little or no conscious control to perform once the intention is formed (Cummings, 2014). Automation is superior in skill-based tasks because such tasks have a clear feedback loop to identify the differences between a desired outcome and the actual result. The rule-based tasks are highly rehearsed by rules, routines, or procedures to select a course of action (Cummings, 2014). Intelligent agents with optimization algorithms work primarily at the rule-based level. However, when faced with uncertainties, automation may not store the relevant information or doesn't include variables that impact the final solution. In this case, humans' high level cognition is required to decide the criteria and weight of an optimal solution. Hereby, the rule-based tasks need the collaboration of humans and automation to create a better solution. The humans' power of induction is critical in the knowledge-based and expertise tasks. Humans' judgement and intuition are essential to deal with the situations where the goal is ambiguous, uncertainty is high and mathematically optimal solutions are unavailable. The induction of humans is difficult for computer programming to replicate, especially the true expertise. Considering efficiency, humans can make use of the intelligent agents' advantages in speed, calculation accuracy, memory and information processing capacity to complete the knowledge-based tasks.

Therefore, tasks can be done by automation, human alone or their collaboration. The collaborative tasks can be further decomposed into sub-tasks that are assigned to and finished by a specific agent, either humans or intelligent agents.

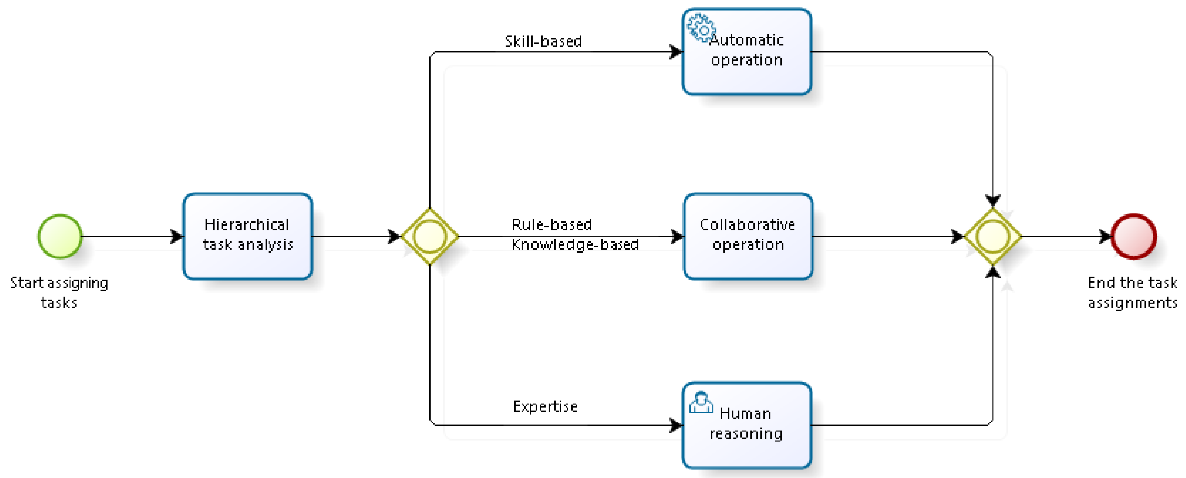


Figure 10 Task assignment

This thesis also modeled the activities of humans and intelligent agents and their relationships in decision making process by BPMN (See Figure 11). Figure 11 clearly presents which task is assigned to which entity, humans or intelligent agents. Also, Figure 11 helps to identify which tasks are accomplished by a human-intelligent agent collaborative work, which are *Generate alternatives, Assess alternatives*, and *Evaluation*. These three collaborative tasks are also the top level tasks identified in Table 7 that need to be divided to sub-tasks. The sub-tasks of each top level task will be further defined by HTA technology in the latter case study.

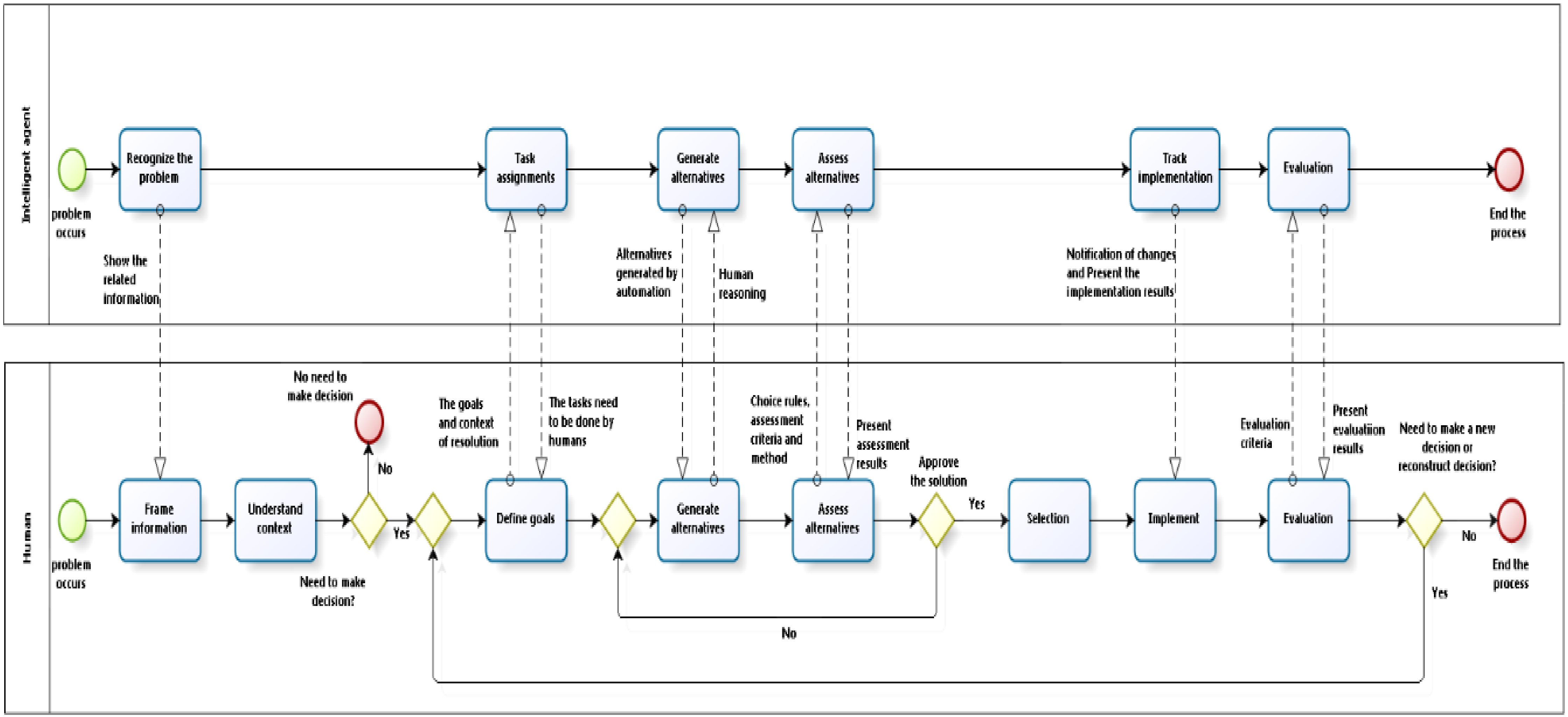


Figure 11 Activities of humans and intelligent agents in decision making process

The task assignment decides the way of generating alternatives (See Figure 12). The alternatives can be come up with automatically, or based on humans' experience, or by the collaboration of humans and intelligent agents.

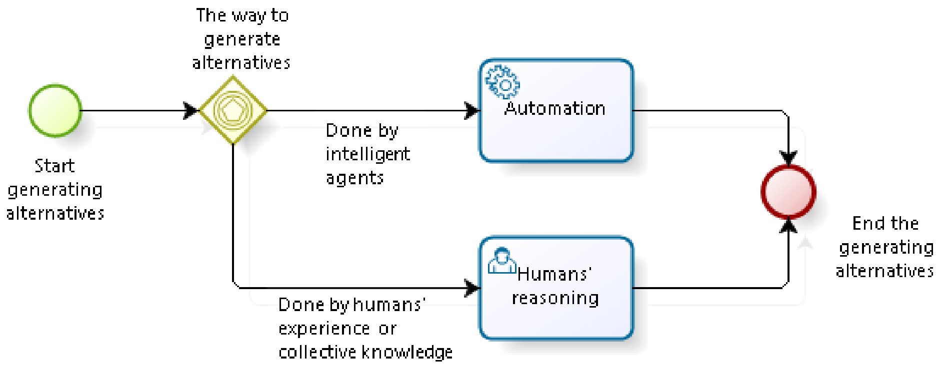


Figure 12 Generate alternatives

Selection phase

Before selecting a solution among alternatives, the decision making process goes through the process of assessing the generated alternatives. The selection rules, selection methods and assessment criteria are decided ahead to meet the defined goal and to narrow down alternatives. After the assessment, there might be no a solution meeting the defined goal. If happens, the process comes back to the *Solution Identification* phase to re-generate alternatives by changing priorities and criteria, or the generation way.

Implementation & Evaluation phase

After selecting a solution, we need to implement it in reality and evaluate the implementation effects. Sometimes, uncertainties and un-recognized variables might happen during the implementation. Thus, it is hard to be certain that the defined criteria are what characters of an optimal solution are. The results of the actual implementation decides whether the selected solution is a right decision. If the selected solution successfully solves the problem and meet expectations, then decision making comes to the end. If not, the process restarts in the *Problem identification* phase to reconsider the problem and make a new decision. Thus, decision making can be a loop process. Besides, there is also a learning process in decision making. The experience gained from the process will feed the knowledge acquisition agent so that the later decision making can constantly benefit from the continuously updating knowledge base.

4. Case study

This chapter introduces a case study for validating the application effects and hypotheses of the IA framework proposed in Chapter 3. The case is about synchromodality. Synchromodality aims to provide a dynamic, efficient and environmentally friendly transport plan to meet the growth transporting demands and the increasing customers' requirements. To achieve synchromodal transport, it needs the interconnectivity of multiple modes and the cooperation between the involved actors in the transport network.

4.1. Problem statement

Section 2.1.4 identified three attributes of the problem that is suitable for IA application, that is, high cognition, high efficiency and high uncertainty. Thus in this section, we are going to analyze synchromodality under these three attributes to figure out: 1. whether IA is applicable in the synchromodality area, 2. what problems needs to be solved in the synchromodality circumstance.

High cognition:

Synchromodality integrates transport services to achieve customization and responsiveness. With the increasing customer requirements on logistics service, there are multiple goals for synchromodal transport to achieve at the same time. Synchromodal transport should be efficient, flexible, reliable and sustainable meanwhile keeping the cost at an acceptable level. Hence there are many factors to be considered in order to have a synchromodal transport, such as, capacity, operating time, CO_2 emission, dynamic planning and operating cost, etc. Customers have different emphases on these factors or services. To interpret and meet customers' demands, the synchromodal transport planning needs humans' judgement and cognitive capability to define the goal of and the rules of transportation planning.

Besides, the collaboration between stakeholders, like information sharing, is the primary basis to achieve synchromodality. There is a need to shift stakeholders' minds and enhance their awareness of cooperation. Synchromodal transporting requires the involved actors a joint-effort to communicate, exchange and share information between each other, which needs humans' cognition and awareness to integrate both explicit and tacit information in the transport network.

High efficiency:

To achieve synchromodal logistics, it is necessary that decisions are made during the process execution, not only in the design phase. Therefore, synchromodality requires to collect the needed data as fast as possible to support transporting planners' decision making. However, the information exchange and integration between stakeholders is hampered by the fragmentation of data, lack of standardization and agreements, incompatibility of information systems and security issues. Besides, to get an optimized solution, the synchromodal transport system should generate more alternatives for decision makers to choose, which increases the demand for the computer aided planning. From studies, intelligent transport system (ITS) and information communication technology (ICT) are major solutions to facilitate the information exchange within the transport network by providing data visibility, accuracy, transparency and security at a highest possible level.

High uncertainty:

There is a high frequent occurrence of unexpected disturbances in transportation, for instance, extreme weather events, traffic congestion and new incoming orders. Synchromodality offers great flexibility to cope with these uncertainties through real-time modes switching according to the available capacity and actual circumstance so as to meet customers' requirements on reliability and responsiveness. Besides, the demand pattern is not easy to be predicted so that the transport planning needs a dynamic plan to adjust the transportation arrangement according to the real-time demands and modes capacity.

Moreover, there are many challenges to achieve synchromodality. For instances, the approaches of an optimized synchromodal planning, architecture of integrated network, the design of physical network, information exchanging mechanism, criteria of cost, service and quality, and legal issues etc.

Thereby, synchromodality is a good candidate to prove IA's practical values in decision making. One of challenges in synchromodality is to achieve and offer great flexibility in its transport network planning. Thus this thesis applies the proposed IA framework in synchromodality's real-time network planning. The validation aims to prove whether IA helps synchromodality achieve flexibility in creating an optimal transport planning and adjusting the plan within limited time as soon as new information arrives (like new orders) or unexpected disturbances happen, in the meantime meeting customers' demands and satisfying their requirements.

4.2. Serious game

The serious game simply exploits an informal, incidental and unconscious way to help people acquire skills, knowledge, or attitudes by using computer games (live-simulations or virtual environments) (Korteling et al., 2011). These computer games framework certain aspects of reality with a didactical goal through combining simulation, learning and play (Korteling et al., 2011). According to Korteling et al (2011), using a serious game is a promising approach in training or education when other methods are unattractive, expensive or have impose unacceptable risks for the learner or the environment. Therefore, considering the expenditure of time and effort in a real business case, this thesis chooses the serious game approach to validate the practical value of IA and the applicability of the designed IA framework.

This thesis uses the serious game SynchroMania developed by TNO, a Dutch research organization. The SynchroMania (PPMC, 2014) simulates the real operations of synchromodal transport planning. In the game (See Figure 13), the player takes a role as a logistics planner to ship the orders placed by three clients to various locations within a container hinterland network. At the planning desk of synchro transport services, the timetable represents one week. Every day has new orders coming which need to be assigned to one of transport services. Each order has specific requirements of dates, locations, modes and demands imposed by the client. During planning, the planner must strive to satisfy the client's specific requirements while lowering the overall cost and emission level within the time restriction.

From Figure 13, you can see that there are three locations: North, South and Destination which create five transporting routes (see Table 8). By Route 1, 2, 4 and 5, the cargo can be delivered by three modes: Truck, Train and Barge, while Route3 only allows trucks to transport orders from port to destination. The cost of each mode is described in Table 8. Barge is the cheapest transportation followed by Train and Truck sequentially. The "committed" in Table 8 means the space is already pre-booked and pre-paid, which is displayed with gray background in the timetable. If a player uses the committed space, there is no additional cost. In the timetable, the rest of numbers without background represent the “uncommitted” space which means the cost is incurred per use. Figure 13 also illustrates that there may be limited or no capacity of Train and Barge in a day, while, the direct trucking has unlimited space in week days. If the order cannot be scheduled because of no available capacity, the planner can negotiate with customers whether they agree to switch modes, change dates or locations. At the end of each round, the game shows the results of the weekly transport plan about the unshipped and shipped volumes, cost, CO_2 emission level and customer satisfaction.

Figure 13 Serious game SynchroMania

In this thesis, the performance indicators of transport planning in this serious game SynchroMania are:

- Cost per TEU
- Client satisfaction level
- % volume transported
- CO_2 emission level

That is, the transport planning in this serious game aims to minimize the transport cost, meanwhile keeping a high client satisfaction level and saving the environment as much as possible. To reduce costs, the planner is advised to use more Barge and Train, try to fill in the already paid committed space, and avoid the direct trucking. The increasing utilization rate of Barge and Train helps to reduce the CO_2 emission. The customer satisfaction level will be increased when the customer’s orders are delivered on time, while, per request to negotiate with the customer decreases the customer satisfaction level.

Table 8 Transporting routes and costs

Route	Truck costs	Train costs committed	Train costs uncommitted	Barge costs committed	Barge costs uncommitted
1. Port-North (direct)	300	0	100	0	90
2. Port-South (direct)	300	0	100	0	90
3. Port-Desti (direct)	400	-	-	-	-
4. Port-Desti (via North)	-	100	200	100	190
5. Port-Desti (via South)	-	100	200	100	190

4.3. Decision making process

The problem context of this SynchroMania game is easy and clear to be understood. That is, the player needs to make a transport plan when new orders come. The goal of planning has been clarified in Section 4.2. Thus, the first phase of decision making – *Decision Identification* is simplified as Figure 14 shows. Next the task assignment of humans and intelligent agents is analyzed based on the context of SynchroMania game. In Figure 14 , *Generate initial transport planning* is the process to make an initial transportation plan on the basis of customers' requirements, which represents the process of *Generate alternatives* in Figure 7 Decision making process. The assessment and approval of solutions in Figure 7 are simplified as the process of *Optimize plan* that adjusts the initial plan to achieve the goals defined beforehand. The task assignment decides the sub-tasks of the processes of generating and optimizing the transport planning.

Then selecting a best transporting plan is the end of *Selection* phase. In the final phase of decision making in Figure 14, there is no loop back to the beginning phase. That is because players cannot (re)-arrange the orders in the past days. But decision makers can gain experiences and adjust the decision making strategy through analyzing the results of the weekly planning with performance indicators to improve the next round planning.

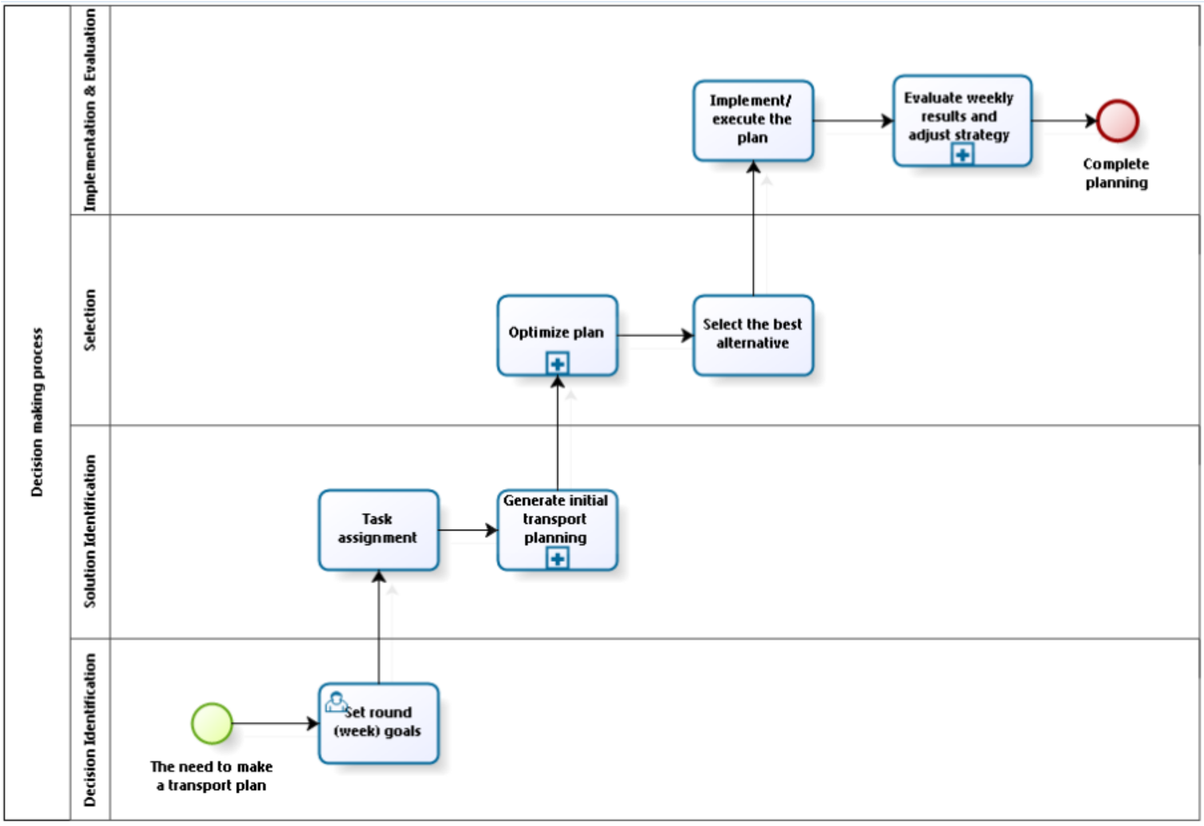
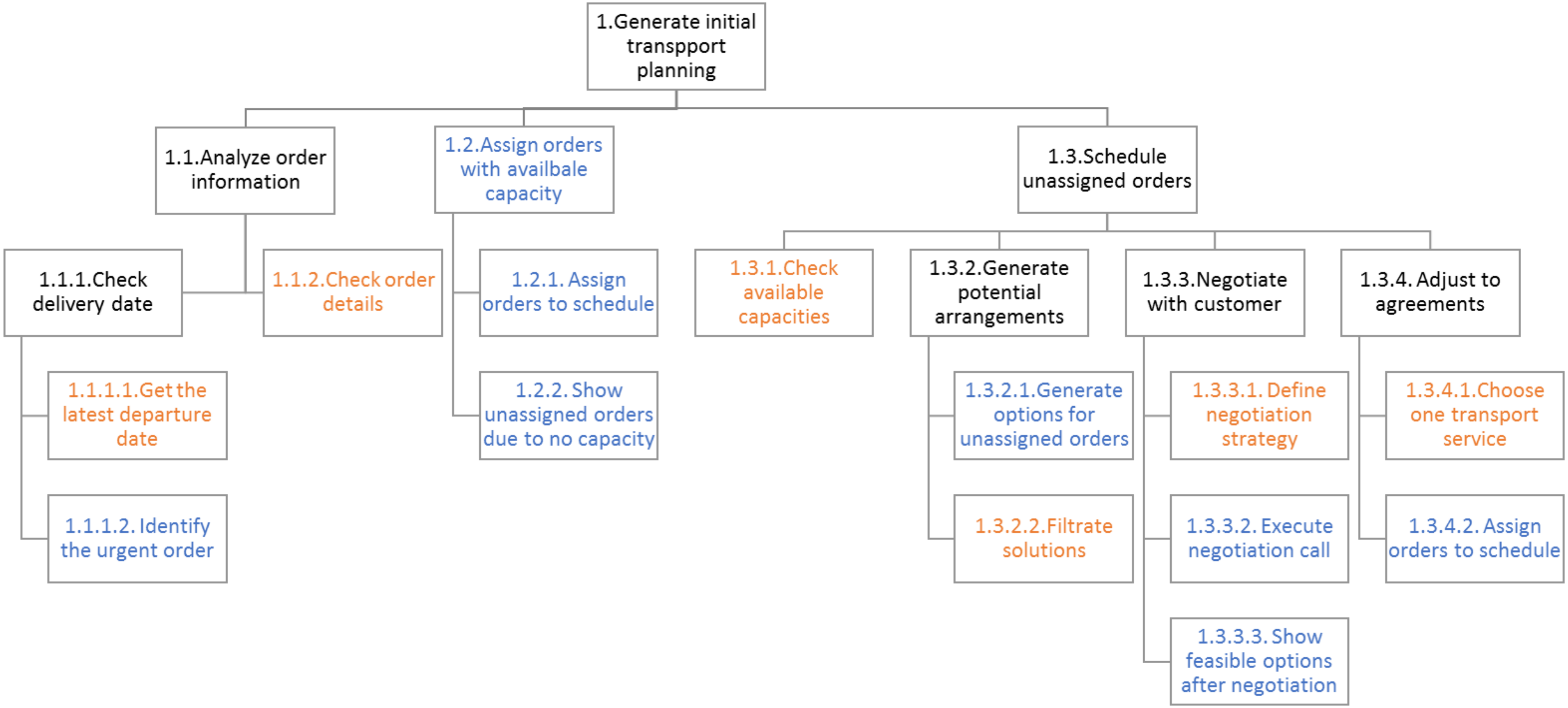


Figure 14 SynchroMania transport planning decision making process

4.4. Tasks assignment

This thesis adopts the hierarchical task analysis (HTA) method to decompose the top level tasks that are about generating, optimizing and evaluating the transport planning. The decompositions of these three top level tasks are respectively described in Figure 15, Figure 16 and Figure 17. The tasks in blue are advised to be completed by intelligent agents, while the yellow one means the tasks for humans. Some second or third level tasks are in black, which means they are collaborative tasks completed by the cooperation of humans and intelligent agents. These collaborative tasks are further divided into sub tasks that can be assigned to a specific entity, either humans or intelligent agents.

From the task decomposition by HTA method, the task allocation of humans and intelligent agents in this SynchroMania game becomes apparent. The tasks allocated to humans also manifest humans' importance in the decision making of SynchroMania transport planning. We can further base on this result of task assignment to build the intelligent agents that are able to cope with the tasks assigned to them.



Black: collaborative tasks
Yellow: tasks for human;
Blue: tasks for intelligent agents;

Figure 15 Task decomposing of generating transport planning

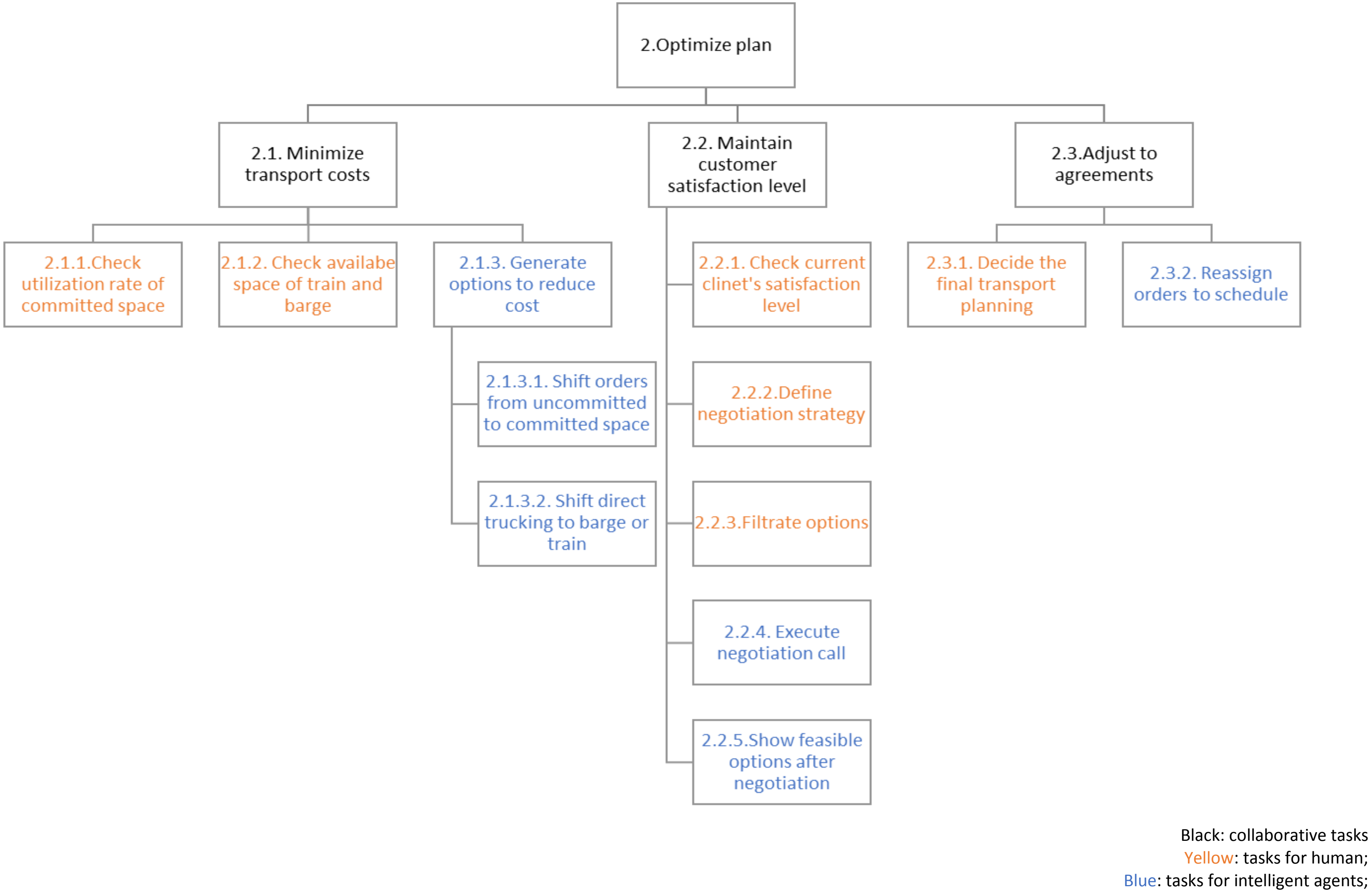


Figure 16 Task decomposition of optimize transport planning

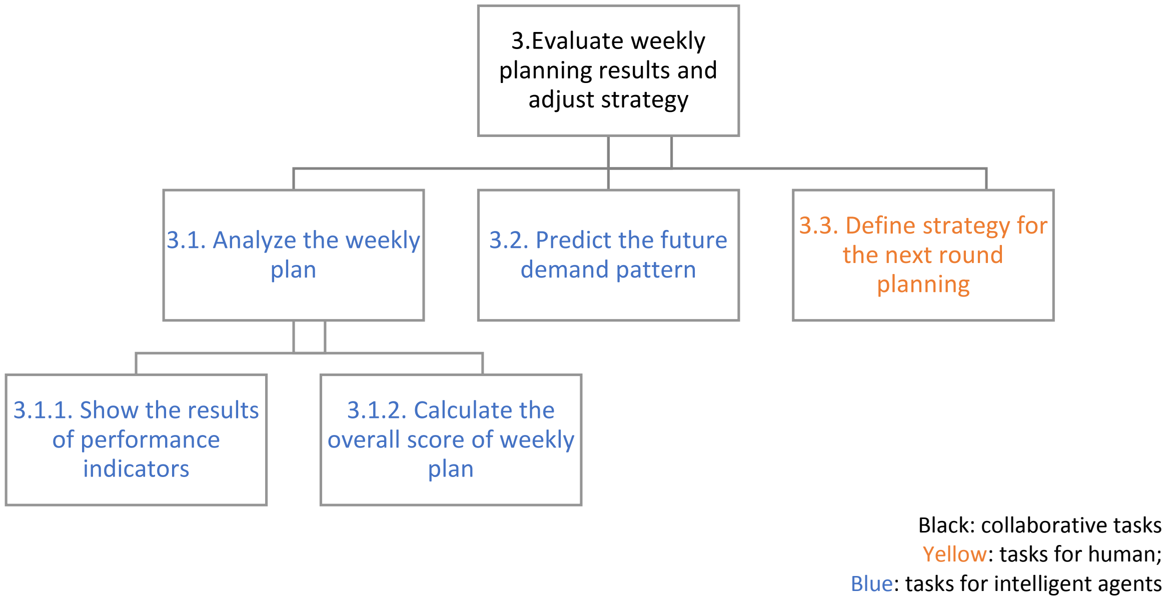


Figure 17 Task decomposition of evaluation

4.5. Intelligent agent

Based on the result of the tasks assignment in last previous section, the requirements and functionalities of intelligent agents are defined in order to realize the human-intelligent agent collaboration and achieve intelligence amplification.

① Urgent order identifier: Identify and highlight the urgent order

Purpose: As the amount of time to make a decision is limited, intelligent agent could assist players in identifying urgent orders.

Action: Upon activation, this agent continuously scans all the orders in the inbox. For all the orders, this agent compares the due date with the current day. If they are same, the agent saves the ID of the order and send a command to the graphics component to display a visual mark next to the order with the given ID.

Input: List of all the orders in the player's inbox (ID and due date); current day

Output: Display a red rectangle at the coordinates where the urgent order is located.

Execution: Continuous. When switched on, this agent continuously runs and highlights urgent orders until switched off by the player.

② Auto assigner: Automatically assign orders

Purpose: In SynchroMania game, the planner needs to drag orders to the timetable while keeping in mind of meeting the order's requirements. The intelligent agent could help reduce the amount of orders by automatically assigning all "clear" cases. The "clear" case is an order with a fixed mode and for which there is available capacity / space to ship this order. This functionality helps save time so that planners can make and execute decisions efficiently.

Action: When activated, Auto assigner checks all the orders in the inbox. For each order, this agent knows about the information about destination, modality, time and TEU. Then this agent checks the capacity for the given destination and the given mode in the first possible day. The process will be repeated for the remaining days. If there is capacity available, Auto assigner assigns the order to the appointed spot of the timetable. If not, the order will be ignored.

Inputs: List of all the orders in the player's inbox (ID, destination, mode, first day, due date, TEU); Current day; list of available capacities per destination and per transport mode.

Output: Call to the game function that allocates an order from the inbox to the timetable

Execution: Continuous or One shot. The agent either could be set to one shot that executes players per call or continuously checks all inbox orders and try to assign them until no orders are left in the inbox or the order's requirements cannot be satisfied.

③ **Alternative advisor: Generate alternative options**

Purpose: The intelligent agent could generate alternatives for the order currently under the player's consideration and inform the player other options to assign the order. Especially when there is no capacity to meet the requirements of the order, this intelligent agent could present options for these unsatisfied orders and show the options to the player.

Action: Once activated, this agent will be given the ID of the order currently considered by the player. For that ID, this agent checks if there is capacity to assign the order along its requirements and the client's preferences. Alternative advisor also checks if there is capacity available for other options in case one of the parameter is changed, for instances, changing modality, destination, or delivery dates. If the check returns positive answer, a transparent icon is displayed at the appropriate position within the schedule, highlighting the component that has to be negotiated with the client.

Input: Order under focus (ID, destination, mode, first day, due date, TEU); list of available capacities from schedule per destination, per transport mode and per day.

Output: Call to the game function that displays an order icon (preferably semi-transparent) at given X, Y coordinates, followed by another function call to draw a red rectangle. And also call to the game function that assigns orders to the position of the timetable.

Execution: One shot. This agent is executed per call by the player and only works when there is an order under consideration.

④ **Negotiator: Negotiate with customers**

Purpose: To relieve planners from taking time to communicate with customers, the intelligent agent could take charge of calling customers and negotiating with customers about the parameter (mode, location or due date) that is decided by planners.

Action: For each parameter (Location, mode, first day, and due date), there is a corresponding negotiator to be responsible for. Planners will decide to active which negotiator. Once activated, this agent is given the ID of the order currently considered by the player. For that ID, this agent negotiates with the client on the relative parameter and in return, shows planners the negotiation result.

Input: Order under focus (ID, destination, mode, first day, due date, TEU)

Output: Call to the game function that triggers negotiation for a given order and for a specific parameter.

Execution: One shot. This agent is executed per call by the player and only works when there is an order under consideration.

⑤ **Optimizer: Optimize the transporting plan**

Purpose: Once all the orders are placed in the schedule, planners still need to consider whether the transportation arrangement meets the goal of lowering cost. That is where the intelligent agent may contribute to. The rules of optimization algorithm can be:

- Maximize the utilization of the committed space
- Reduce the direct trucking
- Maximize the utilization of Train and Barge

Action: This agent enumerates the cost of all the assigned orders and then checks the available capacity and customer's preferences. With the optimization algorithm, Optimizer proposes new options of re-assigning orders to planners for the sake of a low cost. The options are displayed at the appropriate position within the timetable, highlighting the component that needs to be negotiated with a client. After players choosing an optimization plan, this agent re-allocates the order to the schedule.

Input: List of all the orders already assigned to the schedule (ID, destination, mode, first day, due date, TEU); Current day; list of available capacities per destination, per transport mode and per day.

Output: Call to the game function to display order icon (preferably semi-transparent) at given X, Y coordinates followed another function call to draw a red rectangle. After players selecting a new shipping plan, call to the game function that removes an order from the schedule followed by the call to another function that assigns the order to the new position within the schedule.

Execution: One shot. This agent is executed per call by the player and only works when there is an order under consideration.

⑥ **Predictor: Prediction**

Purpose: The intelligent agent could augment planners' knowledge base for the sake of a good decision making strategy through providing planners with the analysis results of the weekly plan and an estimation of future demand pattern.

Action: On the one hand, Predictor calculates and shows the overall score of each week transportation arrangement. On the other hand, this agent loads the history order data from the game and predicts a demand pattern as a reference for the future transport planning. The information of the demand pattern provided by Predictor is about the weekly pattern of arrival orders, the characteristics of client's behaviors and the features of client's orders.

Input: All the historical order data (ID, client, destination, mode, first day, due date, TEU, and client's preference); the weekly transporting plan

Output: Call to the game function that extracts and calculates the results of performance indictors from the game. And call to the game function that shows the results of the weekly plan and displays the demand pattern.

Execution: Continuous. This agent continuously shows the calculation results after finishing each round and shows the analysis results of historical data before the start of a new round.

The intelligent agent ③ Alternative advisor, ⑤ Optimizer and⑥ Predictor all require a knowledge base so as to produce more feasible options and useful information. To keep updating the knowledge base, these intelligent agents record and analyze every week's transporting plan, specifically analyzing the planner's decision making strategy and the characteristics of the client's behaviors. Therefore, there is a learning mechanism in this SynchroMania IA system that intelligent agents learn from humans to integrate the humans' tacit knowledge with explicit information. This learning mechanism enables intelligent agents to propose better suggestions to planners. With the intelligent agents' effective assistance, planners could be able to make a better decision on transport planning in comparison to when they work alone. This mutually beneficial and collaborative relationship embodies the IA concept in SynchroMania decision making.

Table 9 presents a clear connection between these six ideal intelligent agents and the tasks assigned to intelligent agents by HTA method.

Table 9 Connection between intelligent agent's functionalities and tasks

Intelligent agent	Tasks of intelligent agents
① Urgent order identifier	1.1.1.2. Identify the urgent order
② Auto assigner	1.2. Assign orders with available capacity
③ Generate alternative options	1.3.2.1. Generate options for unassigned orders 1.3.3.3. Show feasible options after negotiation; 1.3.4.2. Assign orders to schedule
④Negotiate with customers	1.3.3.2. Execute negotiation call; 2.2.4. Execute negotiation call
⑤ Optimize the transporting plan	2.1.3. Generate options to reduce cost 2.2.5. Show feasible options after negotiation 2.3.2. Reassign orders to schedule
⑥Predictor	3.1. Analyze the weekly plan 3.2. Predict the future demand pattern

4.6. Testing method

Due to the time limitation, this thesis tests three intelligent agents instead of all six. Urgent order identifier, Auto assigner and Predictor are tested in this thesis. The hypothesis of testing are:

Hypothesis: IA improves decision making on SynchroMania transport planning.

This thesis first separately tests these three intelligent agents to test whether their functionalities are defined properly by using the proposed IA framework, and whether they improve planners' performance. For the testing of Urgent order identifier and Auto assigner, there will be two groups: one group with the help of intelligent agent and another without.

Then this thesis compares two group performances and analyzes the testing results. For Predictor, this thesis compares the changes of each planner's performance before and after using Predictor.

Then, based on the results from the separate testing, there will be a final validation that allows players to choose to use which intelligent agent. They can let Urgent order identifier and Auto assigner to function at the same time or to only use one of them. The purpose of the final validation is to test 1) whether the functionalities of these two agents are defined as useful and helpful to each individual, and 2) whether every individual benefits from the application of IA. The testing group are also divided into two groups: with and without the help of the intelligent agent(s).

4.6.1. Performance indicators and weight

The performance indicators and the weight of each indicator are illustrated in Table 10. We use the simple multi-attribute rating technique (SMART) to decide the weight of each indicator. The indicators are assigned 1-5 points to rank their importance with the consideration of the goals defined previous.

As explained in Table 10, the targets of minimizing the transport cost and keeping a high client satisfaction level are equally the most important. The percentage of shipped orders is also important as it is the key factor to increase the customer satisfaction level and meanwhile, it has positive correlation with the cost to some extent. Sometimes, the cost is small when less orders are delivered. In reverse, it could happen that the more orders are shipped, the higher cost will be. Thus, planners need to balance these three factors. The reason to give the CO_2 emission indicator the least weight is because its influencing factors are not clear and obvious to planners, compared with other indicators. So during planning, players are not able to take actions to purposely reduce the CO_2 emission level.

Table 10 Performance indicators

Performance indicators	Importance (1-5)	Weight
Cost per TEU: a_{cost}	5	5/16=0.31
Average customer satisfaction level: a_{satis}	5	5/16=0.31
% TEU shipped: $a_{\%TEU}$	4	4/16=0.25
CO_2 per TEU: a_{CO2}	2	2/16=0.13

4.6.2. Normalization

The data of each performance indicator (PI) has different units. Therefore, this thesis needs to normalize the data of each PI into the same scale which is from 1 to 10 so that we can calculate all the PIs in one formula to get an overall score of the weekly planning:

$$Score_i = a_{cost_i} \times 0.31 + a_{satis_i} \times 0.31 + a_{\%TEU_i} \times 0.25 + a_{CO2_i} \times 0.13 \ (i = 1,2,3 \dots)$$

Equation 1

In order to make the normalization reasonable, the division of scales is based the distribution of the dataset that is gained from three separate tests.

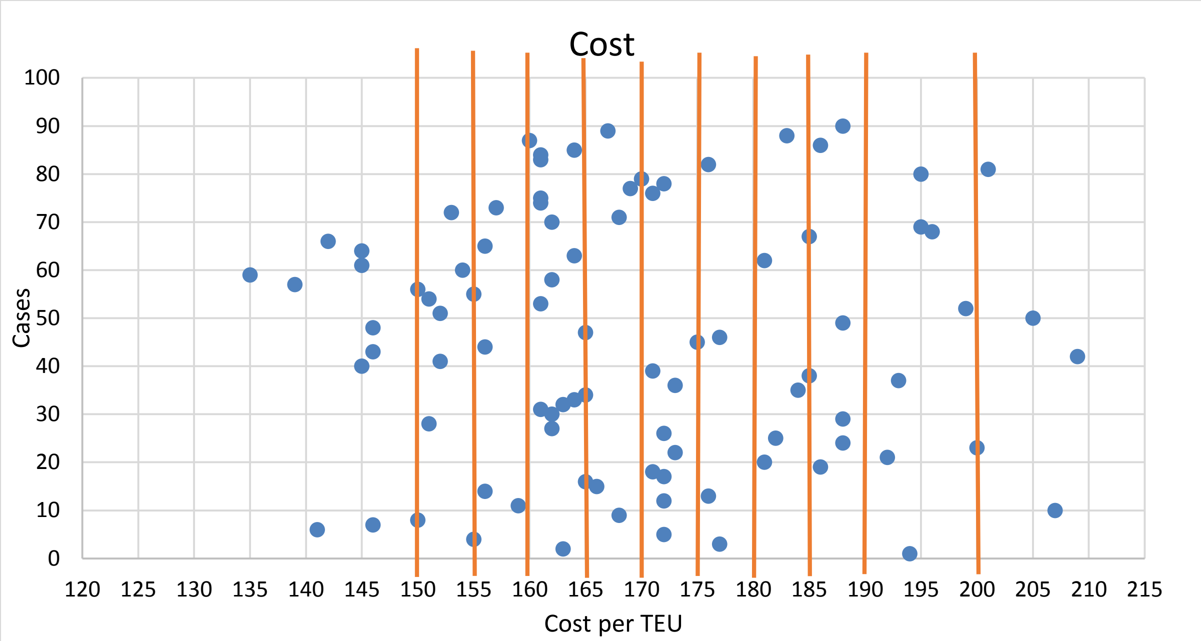


Figure 18 Distribution of cost dataset

Figure 18 presents the ranges of costs generated by per player in different rounds. From Figure 18, it is clear to decide how to normalize the cost into 10 scales. The Table 11 depicts the normalization results.

Table 11 Normalization of Cost

Range of Cost per TEU	Scale
<150	10
150-155	9
155-160	8
160-165	7
165-170	6
170-175	5
175-180	4
180-185	3
185-190	2
190-200	1
⩾200	0

By using the same way, the PI: *%TEU shipped* and the PI: CO_2 */TEU* are also normalized into 1-10 scale. Table 12 and Table 13 respectively provides the normalization results of *%TEU shipped* and CO_2 */TEU* based on the dataset's distribution showed in Figure 19 and Figure 20.

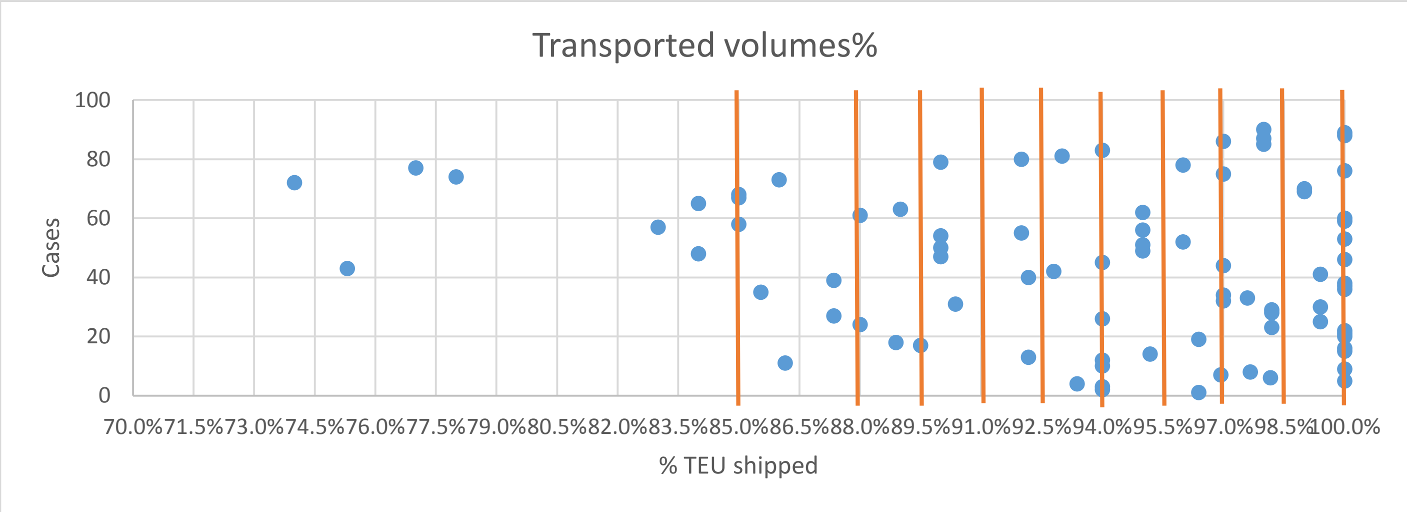


Figure 19 Distribution *of %* TEU shipped

Table 12 Normalization of %TEU shipped

Range of %TEU shipped	Scale
100%	10
100%-98.5%	9
98.5%-97%	8
97%-95.5%	7
95.5%-94%	6
94%-92.5%	5
92.5%-91%	4
91%-89.5%	3
89.5%-88%	2
88%-85%	1
<85%	0

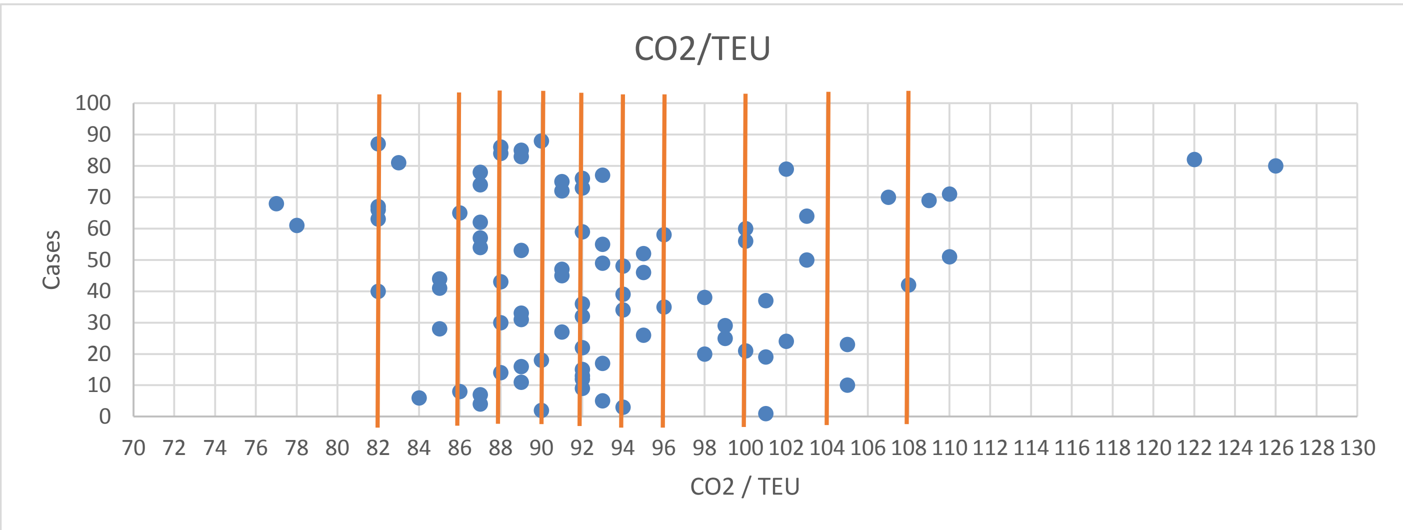


Figure 20 Distribution of CO_2/TEU

Table 13 Normalization of CO_2/TEU

Range of CO2/TEU	Scale
<82	10
82-86	9
86-88	8
88-90	7
90-92	6
92-94	5
94-96	4
96-100	3
100-104	2
104-108	1
≥108	0

For the average customer satisfaction level, each customer has five possible results about their satisfaction level of each weekly transporting plan, which is from 0 to 4. The higher score represents the higher satisfaction level. Thus, 36 possible combinatorics of the average result are generated in Figure 21.

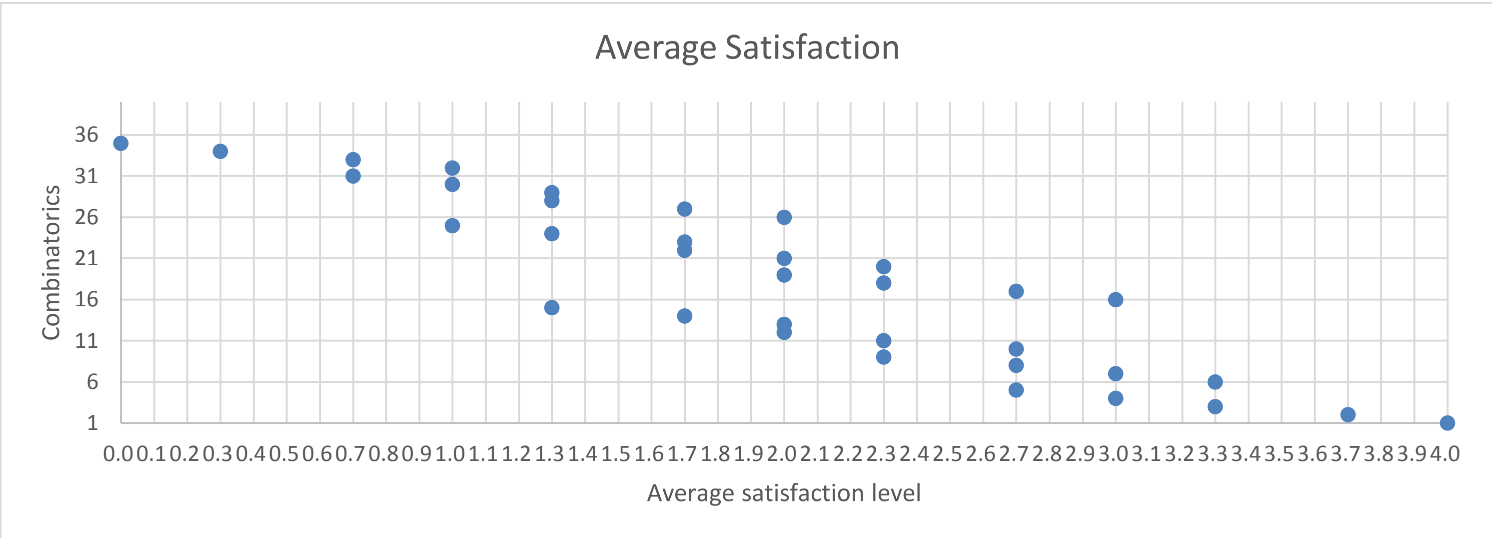


Figure 21 Distribution of average satisfaction level

Hereby, the average satisfaction level can also easily be normalized into 1-10 scales as showed in Table 14.

Table 14 Normalization of average satisfaction level

Range of average satisfaction level	Scale
4	10
3.7	9
3.3	8
3	7
2.7	6
2.3	5
2	4
1.7	3
1.3	2
1	1
<1	0

5. Results

5.1. Urgent order identifier

The Urgent order identifier continuously identifies the orders of which the due date is within the current day and marks the red brackets to give planners the notification. Figure 22 illustrates how the Urgent order identifier works.

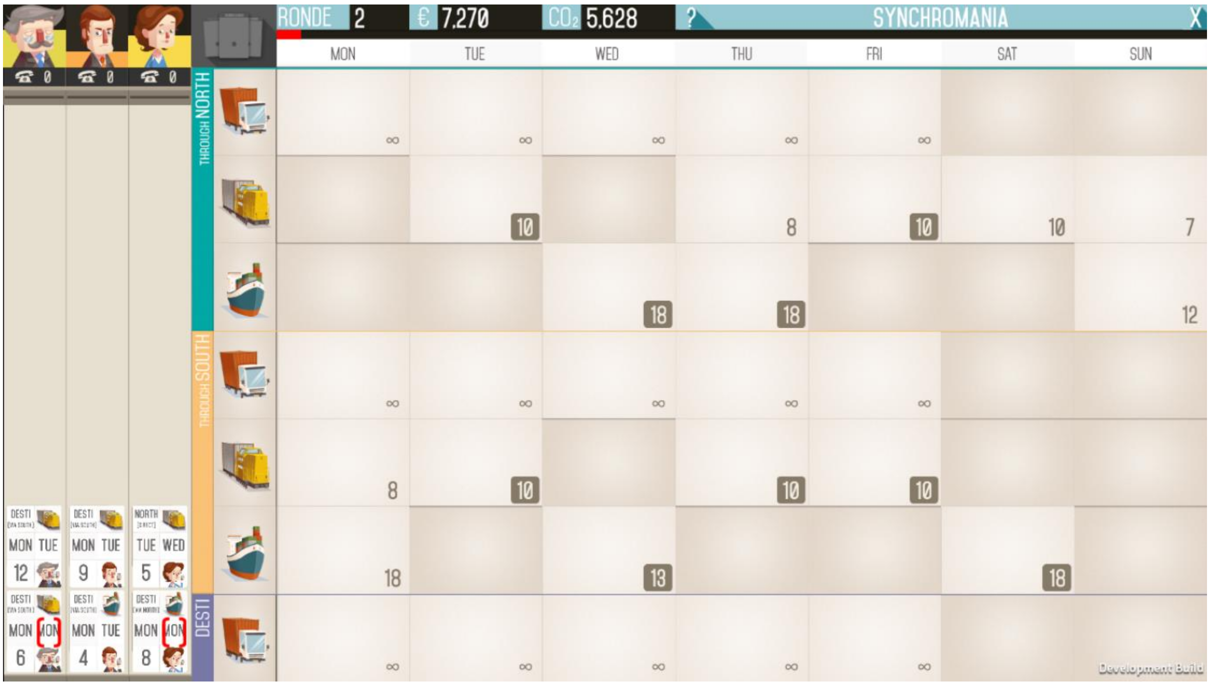


Figure 22 Urgent order identifier

There are two groups (A and B) and two scenarios (1 and 2) for testing the Urgent order identifier. The time of per day is set as 35 seconds in both scenario 1 and 2. The weekly capacity is showed in Figure 22. In each day, there are several orders that need to be shipped immediately. The details of each scenario are described in Appendix. The processes of testing are:

- Group A (4 people) plays scenario 1 without the intelligent agent;
- Group B (4 people) plays scenario 1 with the help from the Urgent order identifier;
- Group B (4 people) plays scenario 2 without the intelligent agent;
- Group A (4 people) plays scenario 2 with the help from the Urgent order identifier.

In total, this thesis got eight pairs of results. The Figure 23 presents the results. The human group represents when players play the game alone without the help of the intelligent agent, while, the results of under the help of the intelligent agent belong to the intelligence amplification (IA) group. All the data are among the normal distribution. The median score of the IA group is 7.65 which is higher than the human group 3.46. 75% dataset of the human group distributed between 2.4 and 4.95 which is evidently lower than the IA group of which 75% is among 7.27 and 9.11. The results of IA group mostly distributed between 7.27 and 7.65, while, the human group's distribution is relatively balanced around the median score 3.46.

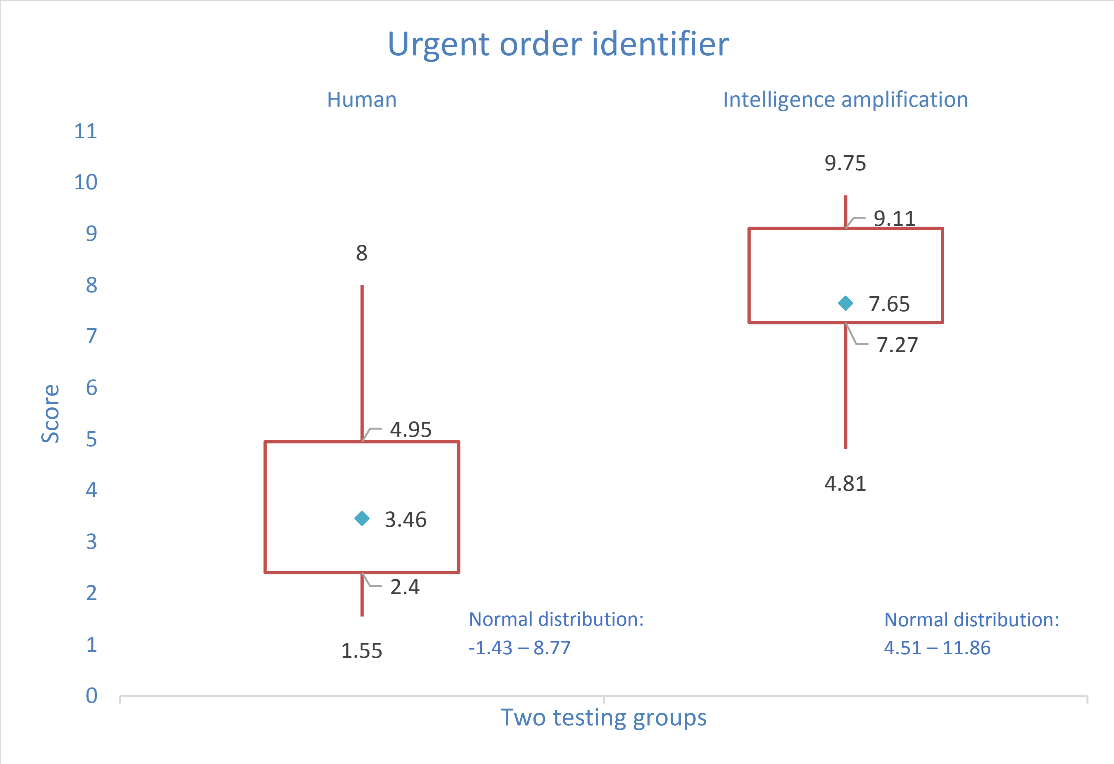


Figure 23 Results of Urgent order identifier

The experienced people who are able to deal with the time limitation can reach a high score when they work alone. The best player managed to reach the score 8. The lowest score in the IA group is 4.81, nevertheless, when this player worked alone in another scenario, the score is higher: 6.25. According to this player's feedback, the red mark of notification made by Urgent order identifier increased her pressure, made her feel more anxious, and disturbed her to make a decision. Since these two score were got under two different scenarios, we cannot directly conclude that this player performed worse with the help of Urgent order identifier. But, we can learn that there is a friction in the interface between humans and Urgent order identifier, which impacts humans' performance. This finding further indicates that the design of intelligent agent varies from person to person. The inappropriate agent design may weaken the individual's decision making. The changes of individual performances before and after using intelligent agent(s) will be further explained in the latter final validation.

In conclusion, Urgent order identifier contributes to improving planners' performance but the degree of benefit varies to different individuals. To produce better collaboration effects, this thesis still needs to find out and reduce frictions of the interaction between humans and Urgent order identifier.

5.2. Auto assigner

When new orders arrive in each day, Auto assigner automatically assigns the orders of which the requirements (mode, TEU, route, and delivery dates) can be met according to the available capacity, and leaves the orders that need the further negotiation with customers to planners. The logic rule of delivery in this agent is to assign orders as early as possible. Figure 24 displays how Auto assigner functions.

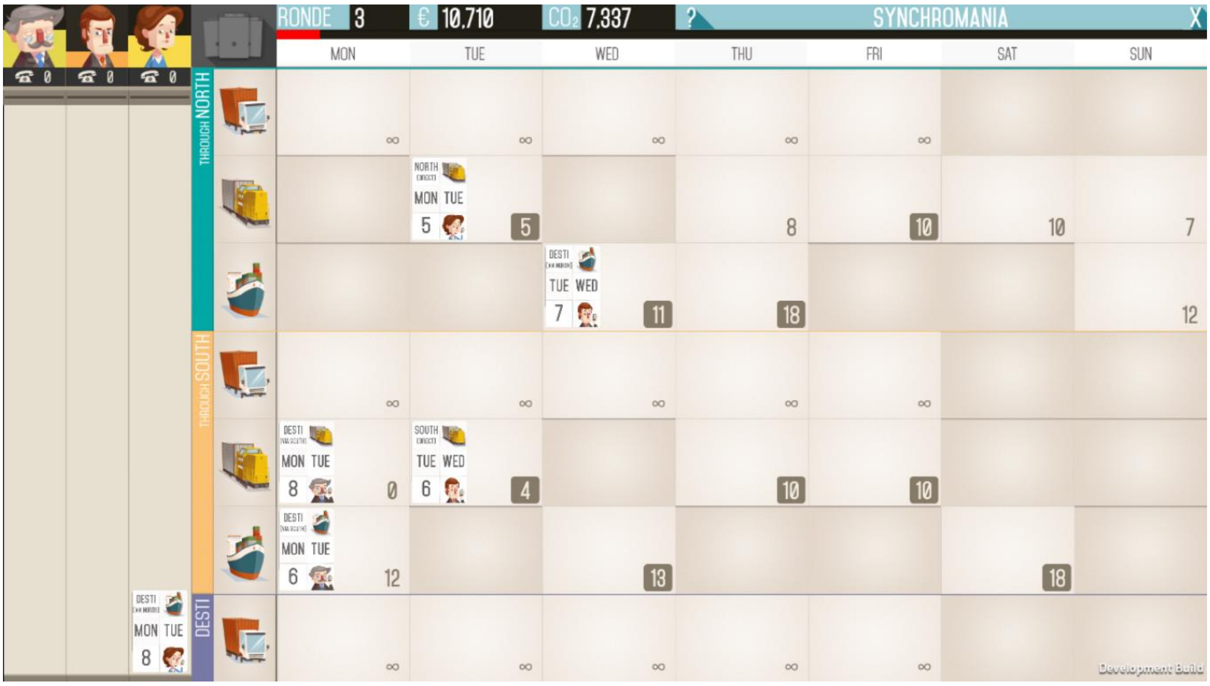


Figure 24 Auto assigner

There are two groups (A and B) and scenario 3 to test Auto assigner. The time of per day is set as 30 seconds in scenario 3. The weekly capacity is showed in Figure 24. Most of orders can be shipped without negotiation. The details of each scenario are described in Appendix. The testing processes are:

- Group A (6 people) plays the scenario 3 without Auto assigner;
- Group B (6 people) plays the scenario 3 with Auto assigner;
- The Auto assigner functions alone

The purpose of the third testing process is to investigate how automation works in this case. When Auto assigner runs alone, the “left” orders with a fixed mode (Barge or Train) will be shipped by Truck when there is no available Barge / Train capacity. That is, orders are assigned as long as there is available capacity. The priority of selecting mode is first Barge and Train, then is Truck. Figure 25 describes the transporting plan made by automation.

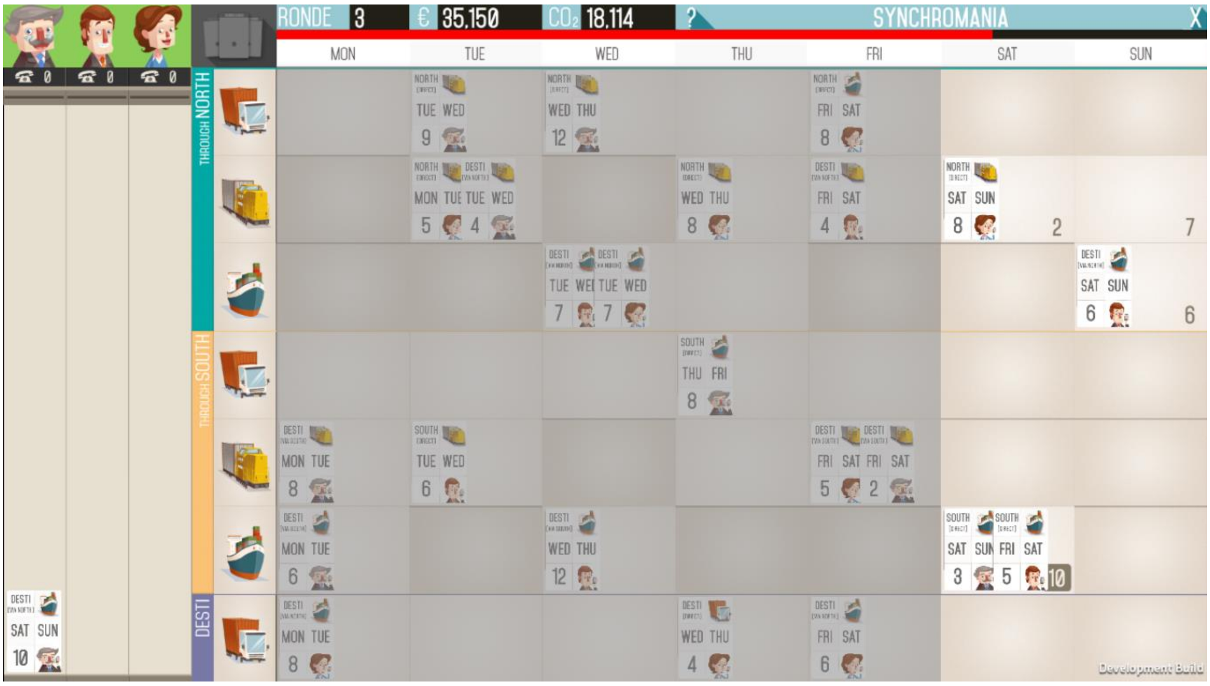


Figure 25 Automation arrangement

Therefore, we got three groups of results depicted in Figure 26. The human group represents when players play the game alone without the help of Auto assigner, while, the results of under the help of Auto assigner belong to the intelligence amplification (IA) group.

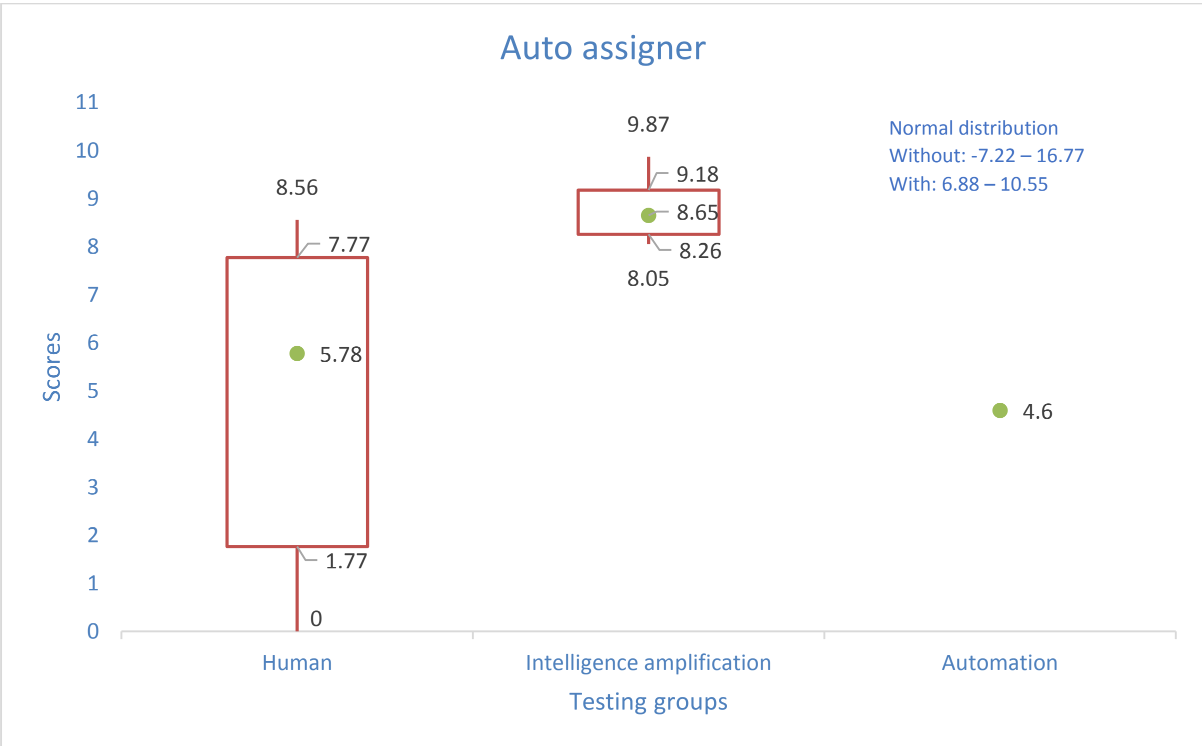


Figure 26 Results of Auto assigner

As we can see from Figure 26, there is a high variation in the human group when decision makers play the game alone without any aid, 75% results ranging from 1.77 to 7.77. That is because of various levels of player's experience in playing this SynchroMania game. With respect to the amount of decision time (30 seconds), the less experienced players felt the time was very limited, whereas, it gave the experienced players enough time to arrange all the orders. The best player managed to reach the score of 8.56 in the human group.

The automation gained 4.6 which is lower than the median score gained by the human group, which is 5.78. This is due to the fact that Auto assigner is not able to negotiate with clients for a better solution and has no knowledge to anticipate behaviors of clients. Nevertheless, humans are capable to handle uncertainties by flexibly negotiating with clients and freeing the capacity in advance for the potential incoming orders. During testing, the experienced players were able to generate a relatively better solution than the automated solution, while the less experienced gained lower scores than automation due to their incapable of dealing with the time constrain.

The group performing best is the IA group, 75% of which ranges from 8.26 to 9.18. The distribution of the IA group performance is concentrated and balanced around the median 8.65 which is much higher than the human group and automation. The minimum score got in IA group, 8.05, is higher than 75% dataset of the human group. This result illustrates that IA benefits players to perform within the range of the best performance.

From the above analyses, this thesis can conclude that Auto assigner considerably improves players' performances which noticeably trend to be within the range of optimization. The testing results also show that in this case, the collaboration between human and intelligent agent performs remarkably better than either human works alone or automation. The main advantages of using intelligence amplification (IA) in this case are that under the time limitation, IA reduces players' workload, assists them to focus on urgent orders and makes them more time to deal with uncertainties so that a better solution can be generated. The changes of individual performance before and after using intelligent agent(s) will be further explained in the latter final validation.

5.3. Predictor

When playing the SynchroMania game, majority of players notice that in the end of week, there is no more available capacity to meet the new coming orders. Predictor presents a demand pattern in the beginning of a weekly planning, which provides players with the tips to improve their decision making strategies, such as negotiating with customers about early delivery to save capacity for future orders. Due to the time limitation, Predictor hasn't been built. In order to prove the Predictor's function, I pretend to be the intelligent agent to give players the tips. The given tips are based on the information that the real Predictor is supposed to provide. In other word, the information that I offer to players is reasonable and can also be feasibly provided by the real Predictor. Assumed in reality, it is easy to analyze the client's behavior based on the historical order data. Therefore, for Ben, a 10-year client, it is highly possible for Predictor to find out Ben's behavior and his orders' features, that is, Ben often orders large barge and agrees to have early delivery. So I convey this information to players and assume that before a new week, players have already negotiate with Ben and he agrees to order his large Barge order early.

Hereby, there are two scenario 4 and 5 for testing Predictor. Both scenarios have 90 seconds per day which leave enough thinking time to players. Scenario 5 puts ahead three Ben's big Barge order, compared with scenario 4. These three orders are displayed in Figure 27, Figure 28 and Figure 29. Based on Ben's behavior, his Barge order can be available in two days earlier.

Therefore, Order1 which shows up on Tuesday in scenario 4 is available on Monday in scenario 5. Order2 and Order3 are available on Wednesday and Thursday respectively in scenario 5, instead of Friday and Sunday in scenario4. The details of scenario 4 and 5 are described in Appendix. That is to simulate the situation when the player gains the information from Predictor, he/she takes action to negotiate with Ben, asking him to order in advance, and gets Ben's agreement, so that the player is able to receive and assign Ben's large Barge order early so that saving capacity for other future orders.

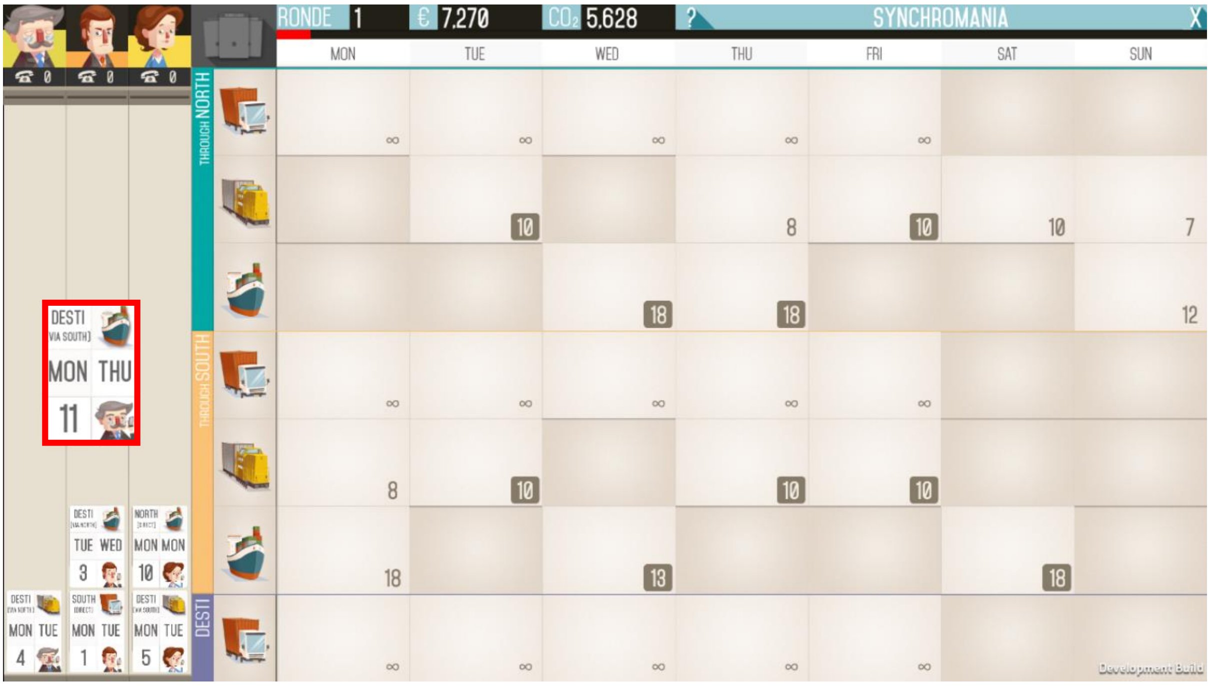


Figure 27 Advanced Ben Barge order1

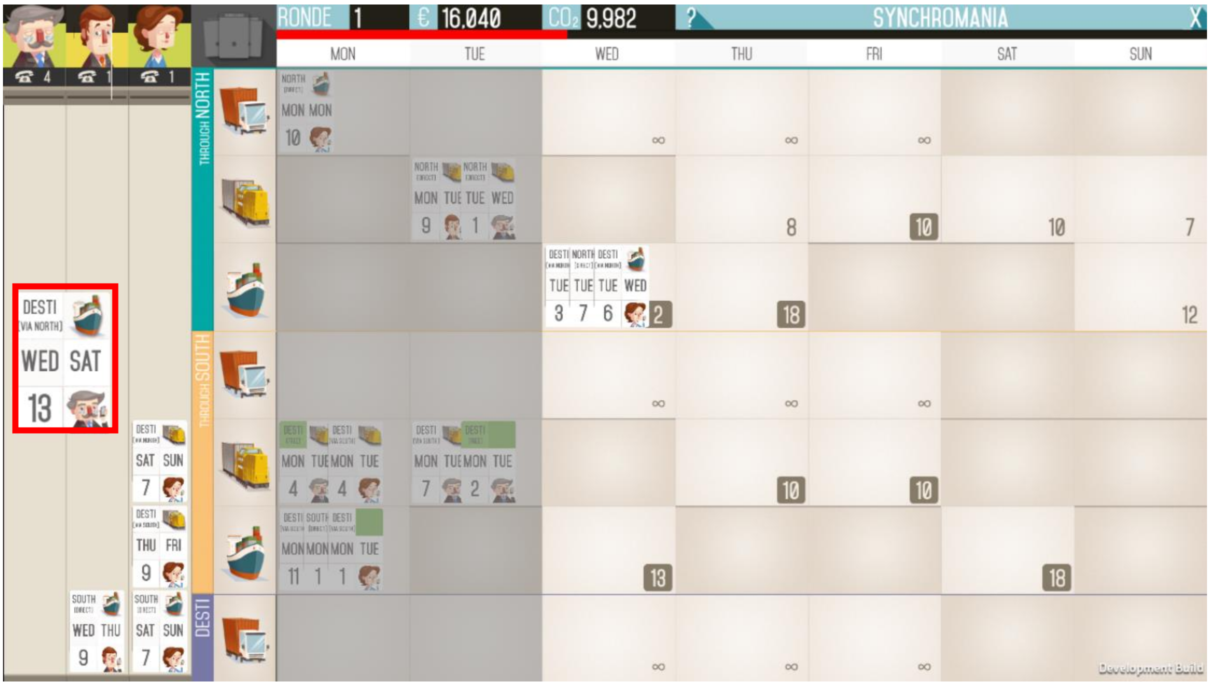


Figure 28 Advanced Ben Barge order2

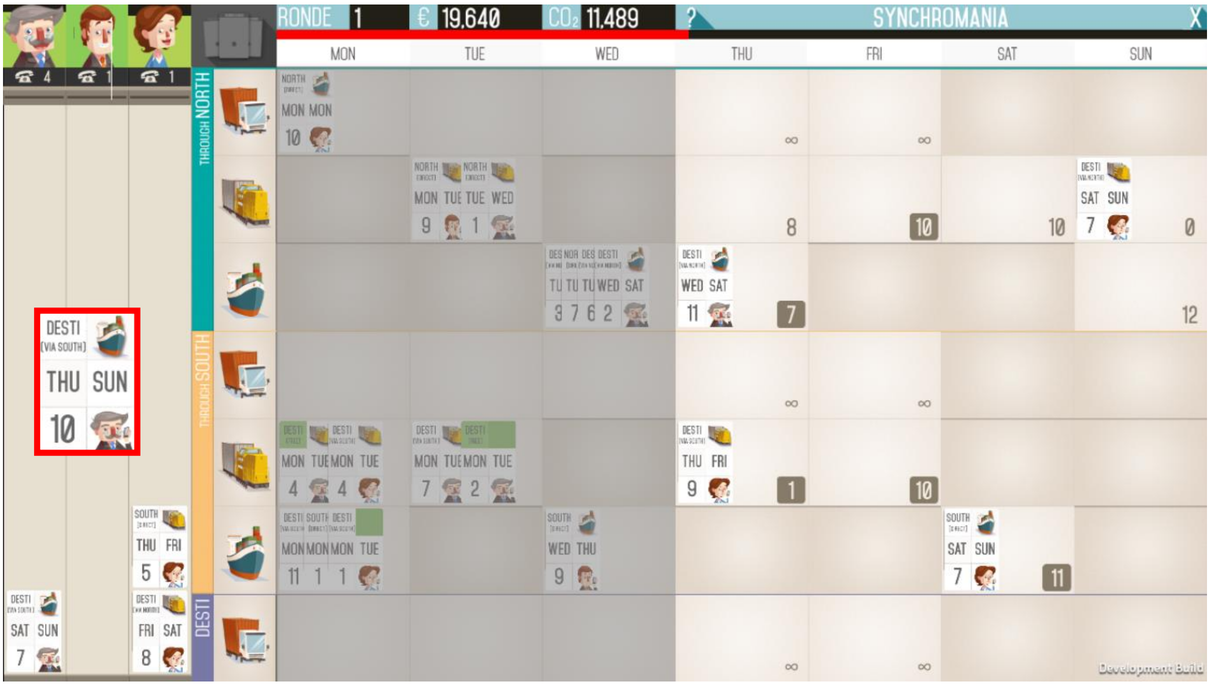


Figure 29 Advanced Ben Barge order3

The testing processes are:

- Group A first plays scenario 4, then plays scenario 5, results are showed in Figure 30;
- Group B first plays scenario 5, then plays scenario 4, results are showed in Figure 31.

This testing is to see whether players will change their decision strategy and make a better planning after receiving the information from Predictor. There is possibility that players may perform better in scenario 5 because of repetitively playing instead of the benefits of having Predictor's information. Thus, there is a need to test the effects of repetition.

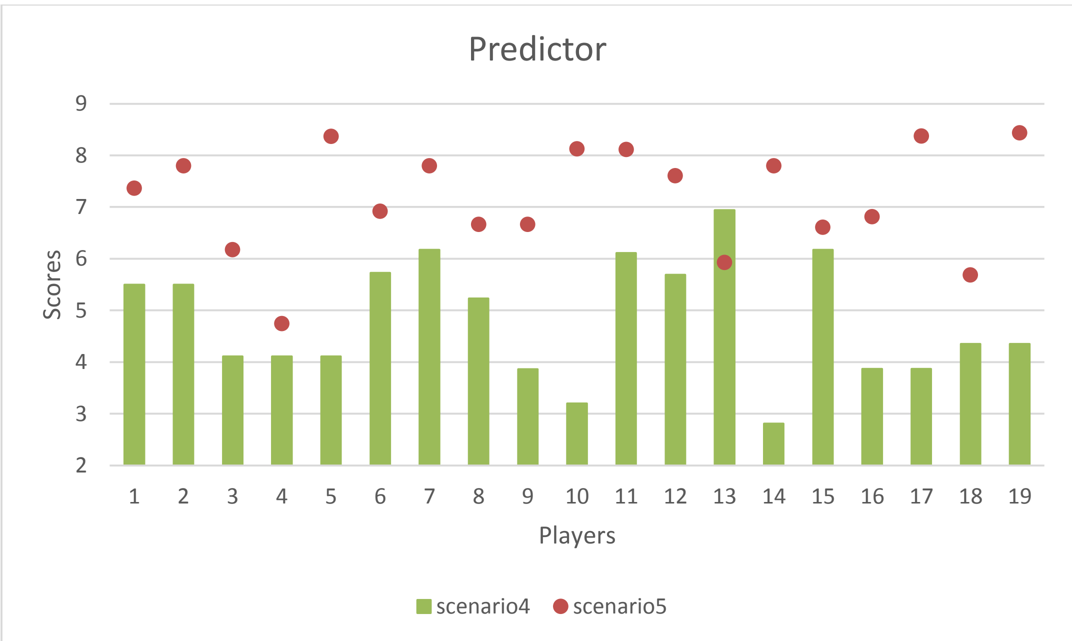


Figure 30 Predictor

As shown in Figure 30, except player13, almost all players have improvements in scenario 5, compared with scenario 4. Some improvements are significant, while, some are slight. The outlier happened because the player's incapable to absorb the tips I gave to him. Overmuch information confused and slowed down his decision making strategy. For instance, instead of shipping Ben's Barge order earlier, he started to ask every order for an early available date, which wasted time and declined the customer satisfaction level. On the other hand, this outlier also tells that repetition is not a direct factor influencing the scores of scenario 5.

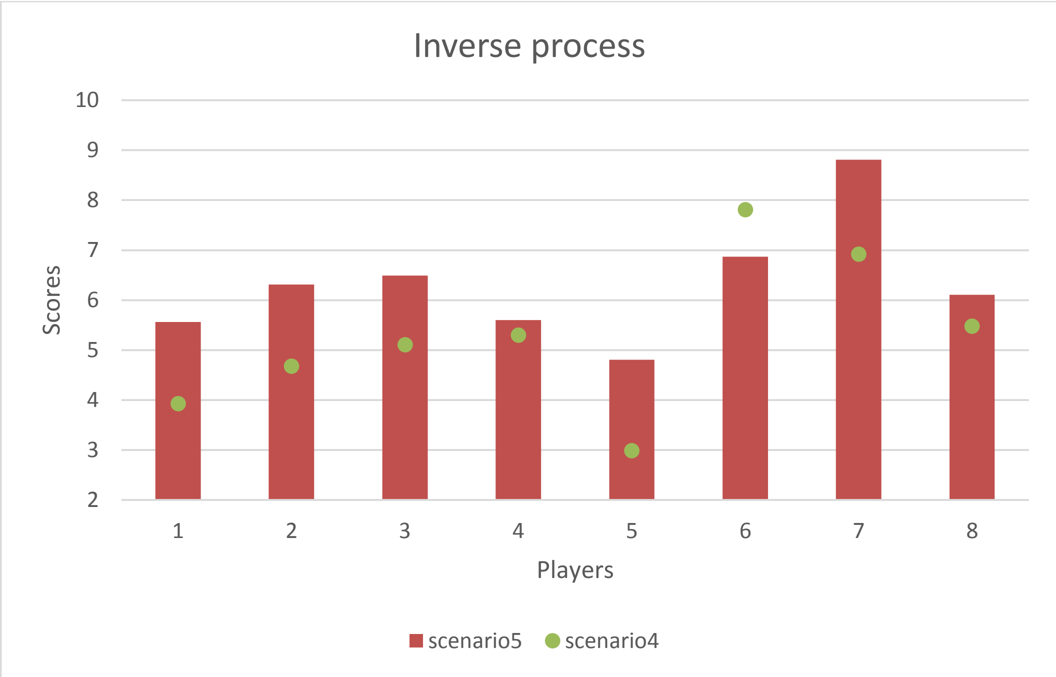


Figure 31 Inverse process of prediction

When conducting the inverse testing, I didn't give any information about prediction to Group B, and just let Group B to play scenario 5 in the first round then scenario 4 for the second round. Figure 31 presents that most players of Group B don't have performance improvements in the second round, expect player6. This result verifies that repetition does impact the scores showed in Figure 30, but doesn't effect a lot. In other word, repetition doesn't decide the improvements of players' performance presented in Figure 30.

In fact, there are also many human factors influencing the testing results, for instances, receptiveness, experience level with this game, learning ability and specially the emotional factors (e.g. nervous and anxiety, etc.). These factors decide that each individual has their unique decision making process. Some players may already realize to save capacity for future orders during the training. Some people may only remember the tips offered by Predictor in the beginning of the game and forget later. In scenario 5, according to players' feedback, a majority of players only assigned Ben's first Barge order1 early which shows up on Monday, but didn't notice the later Order2 and Order3. That explains why some improvements are dramatic whereas some only have slight increases in Figure 30. On the other hand, due to humans' emotional factors, players might feel nervous in the first round and do better in second round when they get familiar with the game. That's why repetition is an influencing factor that cannot be ignored and requires the future testing to completely remove its effect.

Besides, in order to get the real result about how Predictor benefits players' decision making, we need to work out the real Predictor and conduct testing on it. In summary, based on the results in Figure 30 and Figure 30, Predictor can play a role, as catalyst, in improving players' decision making.

5.4. Final testing

There are 14 people joining the final testing which are divided into two groups: Group A & Group B. For intelligent agents: Urgent order identifier and Auto assigner, players can decide to use both at the same time, or only pick up one of two. Two scenarios: scenario 6 and scenario 7 are used for testing. The time of per day in both scenarios is set as 30 seconds. In order to test the changes of individual performances and in the meantime avoid the repetition effect, the two scenarios are played intermittently in four rounds. The testing processes are showed in Table 15:

Table 15 Final testing processes

	Group A	Group B	Automation
Round1-scenario 6	With the help of agent(s)	Without the help of agent(s)	√
Round2-scenario 7	Without	With	√
Round3-scenario 6	Without	With	-
Round4-scenario 7	With	Without	-

Figure 32 presents the results of three groups in the four rounds. The human group represents when players play the game alone, without the help of the intelligent agent(s), while, the results of with the help belong to the intelligence amplification (IA) group.

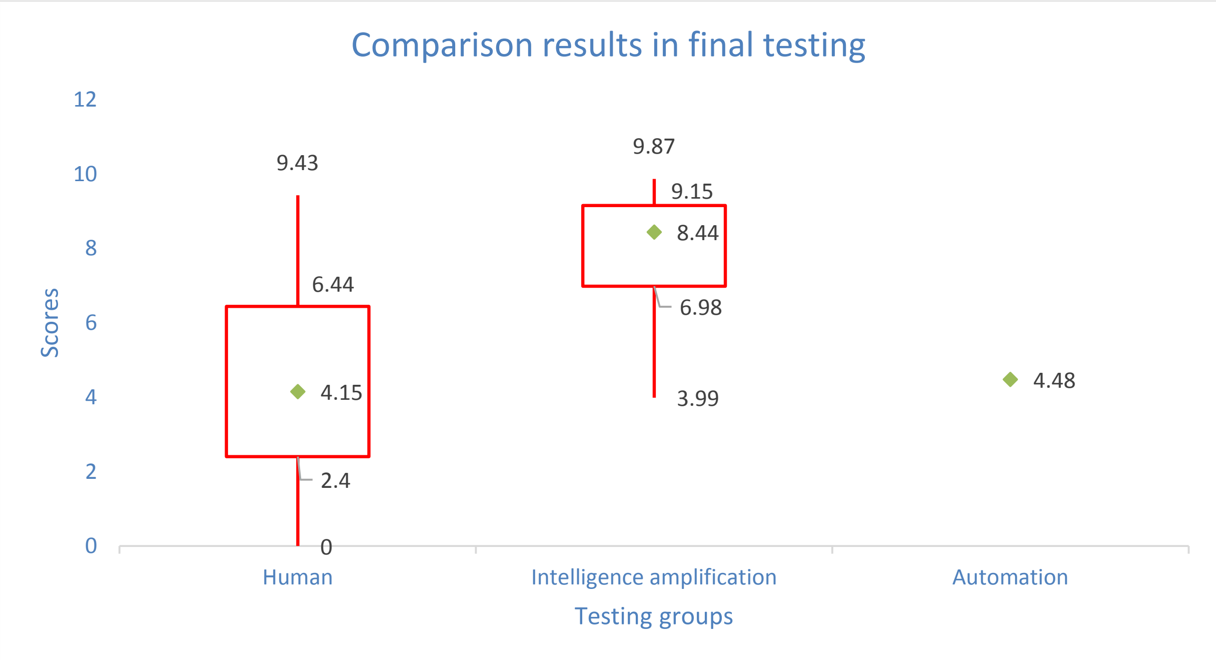


Figure 32 Compariosn results of final testing

Due to various levels of player's experience in playing this SynchroMania game, there is a more variation in the human group, 75% results ranging from 2.4 to 6.4. Experienced players performed better than the less experienced in both two scenarios. Regarding to the time constrain (30 seconds), it is quite limited to the less experienced players to make decisions, whereas, it gave the experienced players enough time to arrange all the orders. The best player managed to reach 9.43 in the human group. The median score gained in the human group is 4.15. The distribution of human group inclines to the right side around and below 4.15.

The average score of automation got in two scenarios is 4.48 which is slightly higher than the median score 4.15 gained by the human group. This is because the automation is superior to humans in efficiently operating routine work. Figure 32 also shows that there are also humans gaining better scores than automation. As discussed in section 5.2, Auto assigner cannot negotiate with clients for a better solution and has no knowledge to anticipate behaviors of the clients. Nevertheless, humans are able to reduce cost, handle uncertainties and arrange an optimal plan by flexibly negotiating with clients and freeing the capacity in advance for the potential incoming orders. Therefore, during the tests, experienced players were capable to generate a better solution compared with the automated solution, while the less experienced gained lower scores than automation because of the difficulty in handling the time constrain.

The group performing best is the IA group 75% of which ranges from 6.98 to 9.15. The distribution of the IA group's performances leans to the left side of the median 8.44. It means the most results of the IA group locate around and above 8.44 which is much higher than the human group and automation.

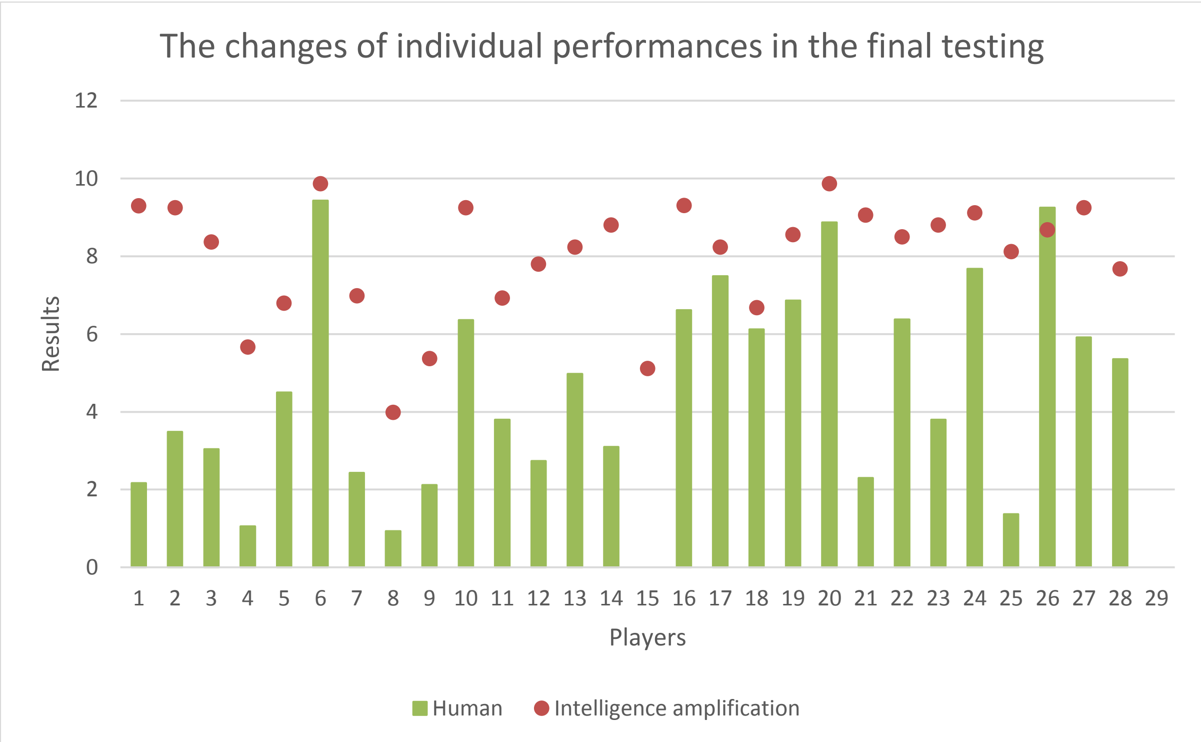


Figure 33 The changes of individual performances in the final testing

To have a clear view about the individual performance's changes, Figure 33 presents the comparison results of with and without using the intelligent agent(s) in the same scenario. In Figure 33, No.1-14 are conducted in scenario 6, and No.15-28 are the results of scenario 7. Almost every player improves their performance by applying IA. Especially for the less experienced players, there is an apparent and significant improvement. The minimum score in IA group, 3.99, is also an improved score from 0.93 gained when the player worked alone.

For the best player, there is also improvement from 9.43 to 9.87. Thus the results indicate when players are experienced enough to work within a short time constrain, the benefits of IA's aids are not so notable.

Besides, as can be seen from Figure 33, there is an exception that the player performed better when she worked alone than working with the intelligent agent, which is 9.25 and 8.68 respectively. This result reflects the adversarial effect produced by IA. The logic of Auto assigner to make a transport planning may be different from humans' decision strategy. Auto assigner schedules orders based on the order's requirements without negotiating with clients and tries to send them as soon as possible without thinking about the cost reduction. In other word, Auto assigner mainly helps to achieve the goal of satisfying clients and shipping as many orders as possible.

For instance, in scenario 6, there are three orders requiring to ship by Truck. When players work alone, in most cases, if there is available capacity, they will choose to negotiate with clients about changing to another cheap and environmentally friendly mode (Barge or Train). Whereas, Auto assigner assigns these orders directly by Truck as the client requires. Most of players didn't pay attention to the automatic arrangement and few players chose to re-schedule those Truck orders.

As we talked previously, humans are superior to machines in generating a better solution in terms of flexibility and creativity. Therefore, if players become fully dependent on Auto assigner, the results can be worse than they play alone. From this point, the relationship of humans and intelligent agents in the IA system, which is summarized in the previous literature review, is not completely correct because the attribute "interdependence" doesn't get support during the testing. On the other hand, this adversarial result also proves that in this SynchroMania game, in order to have an optimized solution, decision making needs to involve human's tacit knowledge and cognitive capability and cannot be replaced by full automation.

Regarding to the usefulness of the intelligent agents defined by the designed IA framework (Urgent order identifier and Auto assigner), except two players, the rest 12 players all chose to use both agents at the same time and all participants stated the aid from intelligent agent(s) made the game easier and evaluated this to be a positive experience. That two players only chose Auto assigner as their assistant. They thought the Urgent order identifier is not much use for them as they could manage the time constrain and the red mark influenced their thinking process. This result hints the challenge of inappropriate interaction design between humans and intelligent agents which is also identified during the separate testing of Urgent order identifier in section 5.1. On the other hand, this result also indicates that the definition of intelligent agents' functionalities cannot be unified. As different people has various decision making processes, the setting of intelligent agent(s) for aiding decision makers could vary from individual to individual. This finding further explains why this thesis promotes a general framework as a reference to apply IA into decision making and leave the details of decision making process based on a specific case.

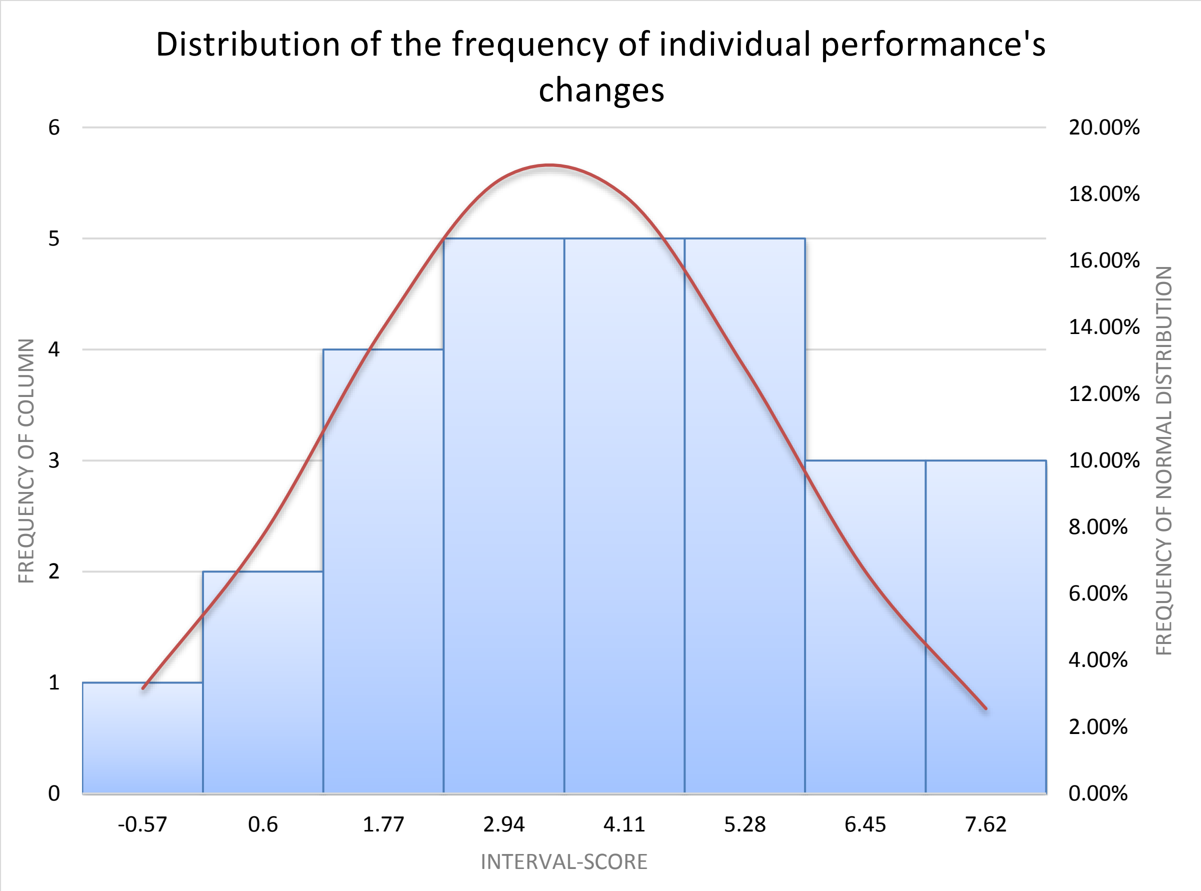


Figure 34 Distribution of the frequency of individual performance's changes

Figure 34 explains the distribution of the frequency of individual performance's changes, which shows a normal distribution. The centralized distribution of the performance's changes is around the average score 3.41. Well the cases that only have slight or negative changes are distributed in the left-most of normal distribution graph. This results show that the cases that IA decreases or slightly improves human's performance belongs to the small probability events. In most cases, there will be significant improvements in the SynchroMania transport planning after applying IA. In other word, the final testing shows a very positive result about IA's benefits in improving player's decision making of the transport planning in SynchroMania.

Moreover, Figure 34 also gives us a good forecast on the positive effects when having a large experimental population and when other intelligent agents are available to be used. Even, this normal distribution result gives us the insights about IA's benefits when IA is applied in other situations, for instance, a real business case in different areas.

5.5. Implication of results

All the testing results illustrate that the collaborative effort of humans and intelligent agent(s) can make a better decision of the transport planning than either humans or intelligent agent(s) working alone in the SynchroMania game. Thus, this thesis can conclude that IA does have positive and significant effects in improving decision making and amplifying human's capability and performance to make a better decision in the Synchromodal serious game. Hereby, the two hypotheses proposed in section 4.6 are proved through the tests.

Besides, the results also indicate the potential benefits if IA is applied in coping with the real business cases in different areas, for instance, the daily transport planning of synchromodality in reality. Hence, IA's potential practical values in improving decision making are also validated through this case study. The extent of the benefits of introducing IA to improve decision making depends on the specific considered problems.

Moreover, the degree of the performance's changes are different from person to person. To achieve the expected IA effects, the setting of intelligent agents should take into account the specific case, the appropriate interaction design, and the individual uniqueness (experience, preferences, or logic process, etc.). Otherwise, the improper setting could generate adversarial effects. Besides, respecting the IA's application, we also need to pay attention to avoid humans to fully depend on the intelligent agent. Therefore, the relationship of humans and intelligent agents in the IA system needs to be redefined as collaborative, complementary and mutually beneficial.

On the other hand, the testing results also validate the usefulness of the designed intelligent agents in aiding players to amplify their capability of making a decision. This positive result proves the appropriateness of the task assignment instructed by the proposed IA framework, which further validates the practical applicability of this IA framework in introducing IA into decision making.

6. Conclusion

This thesis proposes an intelligence amplification (IA) framework to apply IA in decision making. With this IA framework, IA is applied to solve planning problems of synchromodal transport in the serious game environment. This chapter provides the conclusion on the research done in this thesis and answers the research question. Additionally, it discusses the contributions and the limitations of this thesis, and also gives the recommendations for the future work in the related area.

6.1. Answers to the research question

The goal of this thesis is to evaluate the benefits of IA in improving decision making. This is done through exploration on how to apply intelligence amplification in decision making, followed by the artifact design, implementation and finally testing. The design science research methodology (DSRM) was used as the guide

6.1.1. Problem background investigation

The background of the research problem is investigated using the literature review. Based on the results in chapter 2, the conclusion made is that the research of IA is in its infancy. In the current state of the art, there already are many researches taking advantage of the human-computer cooperation effort to complete tasks. But they don't further realize the IA concept. IA utilizes the best of humans and intelligent agents to achieve an effective and right type of collaboration. Besides, some researchers notice the benefits of involving humans in problem solving without emphasizing humans' central role in that. In IA system, humans play the role of the guide to direct and supervise intelligent agents, while intelligent agents act as assistants, aiding humans to fulfill tasks efficiently and effectively. Instead of replacing humans with automation, IA augments humans' intelligence of solving a problem. However, few researches specifically study IA and its effects on enhancing humans' intelligence of problem solving. Moreover, the literature review also indicates that decision making is a good candidate for IA implementation. But, the research of IA has less focused on decision making. Thus, this thesis aims to explore and highlight IA's practical values in decision making as well as whether decision makers' capabilities are amplified by IA.

6.1.2. Design of the IA framework

The lack of the applicable framework for implementing IA highlights the importance of designing an approach on how to apply IA in decision making. Thus this thesis proposes an IA framework. The IA framework introduces six steps of implementing IA in decision making: 1) analysis of decision making process, 2) identification of collaborative tasks, 3) task decomposition, 4) task assignation, 5) design of intelligent agents and 6) implementation. The practical applicability of this IA framework is validated by a case study in the simulated environment using the serious game SynchroMania.

Referring to the designed IA framework, a specific decision making process of the SynchroMania transport planning is defined by the BPMN tool. Through the analysis of the entire process of planning transportation activities, the collaborative tasks in this decision making process are identified. This thesis uses the hierarchical task analysis method to decompose these collaborative tasks into the subtasks that can be assigned to a specific entity, either humans or intelligent agents. Based on the results of the task assignment, the functionalities of intelligent agents are designed to execute tasks that are identified as better suited for the machine. Then, this thesis conducts four experiments to test the usefulness of the designed intelligent agents in improving players' performance.

6.1.3. Validation

IA benefits

The players invited for the test exhibited different skill levels when playing SynchroMania. The experienced players were able to come up with better solutions compared to the purely automated one, while the less experienced had lower scores than automation due to their inability to deal with the time constrain. The IA group where players and intelligent agent(s) work together performed remarkably better than any other group. The main advantage of applying IA in this case is that under the time limitation, IA reduces players' workload, assists them to focus on urgent orders and makes them more time to deal with uncertainties, allowing a better solution to be generated. Thus, player's performance is improved by applying IA. Especially for the less experienced players, there is an apparent and significant improvement.

Test results show that in the SynchroMania, IA does have positive and significant effects in improving decision making as well as augmenting decision makers' capability of coping with time limitation and making a better transportation plan.

Challenges

Exceptions were noted during the testing phase which indicate potential challenges of applying IA. These challenges can cause adversarial effects if not handled.

1) Inappropriate interaction design

In this thesis, the intelligent agent makes a red mark to inform humans about the urgent orders. This design creates friction in the interaction between intelligent agents and humans, weakening decision maker's performance. Some players reflected that the red mark disturbed them and increased the burden. Some claimed that they were feeling pressure or anxiety. Since each individual has its own decision making strategy and preferences, the design of intelligent agents cannot be made to fit all. Besides, more efforts are required in the interaction design to minimize disadvantages caused by the friction.

2) Humans depend on intelligent agent

During testing, few players chose to change the actions made by the machine. This event hints that after introducing IA, humans may become dependent on intelligent agents. In this SynchroMania case, there is a player who performed worse with the help of intelligent agent than playing alone. That is because humans perform better than automation when decisions require flexibility and creativity. Automation places orders based on the order's requirements without negotiating with clients. In contrast, humans flexibly negotiate with clients and can free the capacity in advance for potential incoming orders to better reduce cost and satisfy clients. Hereby, if humans fully depend on intelligent agents, the results can be worse than if they work alone.

Human in the loop

From the test results, decision making process cannot be replaced by fully autonomous operations. Human's tacit knowledge and cognitive capability need to be involved in decision making. This finding further verifies humans' central role in IA system. Thus, for the sake of finding the best possible solution, humans should take the role of manager that 1) define goals and strategies to direct and supervise intelligent agents, 2) deal with special cases and 3) provides creative insights.

6.2. Research Contributions

According to the analyses of testing results, the key contributions of this research can be divided into the theoretical contribution and the practical contribution.

Theoretical contribution:

This thesis proposes an approach, IA framework, to apply IA in decision making. Through the case study, this IA framework shows its effectiveness in solving the task assignment to achieve the human-intelligent agent collaboration through placing humans in the central role of decision making. Concluding from the test results in validation section, the requirements are met to implement IA framework in real case business environment. Besides, this thesis proves IA's benefits in improving decision and shows that IA enhances humans' decision making performance.

Contribution to practice:

This thesis identifies that business decision making is a good candidate for IA implementation. The testing results from the serious game indicate IA's potential benefits in improving decision making in the real logistics environment as well as other related business field. Specifically, the business cases need to make rapid decisions under time constraints and uncertainties, deal with large volumes of data and combine with human expertise. Also, the designed intelligent agents in this thesis give us good insights about what functionalities of intelligent agents we can build to achieve the effective human-intelligent agent collaboration in planning transportation activities.

The approach used to design IA framework in this thesis verifies that process analysis is a good way to explore the collaborative efforts of humans and intelligent agents in terms of the task allocation problem.

The testing results also identify the potential challenges that need to be taken into account. In order to successfully achieve the intelligence amplification of decision making, this thesis suggests that different cases have specific decision making process, thus requiring a unique task assignment to solve this certain problem. The design of intelligent agents should pay special attention to the appropriate interaction design and the individual uniqueness (e.g. experience, preferences, and logic process, etc.).

6.3. Limitations

This thesis investigated three intelligent agents helping players to make better decisions. Including more agents is necessary to know the effects of the full-scale collaboration of humans and intelligent agents in completing the SynchroMania transport planning. Further testing with larger test group is also needed to fully test the effectiveness of the proposed IA framework in assigning tasks of humans and intelligent agents.

The use of the proposed IA framework in applying IA, to a large extent, is influenced by subjective factors. The subjective factors exist in the processes of defining decision making process, analyzing the task assignment and designing intelligent agents. In this thesis, there are also subjective factors in the calculation of performance impacting the testing results. The weight and the normalization of each performance indicator are decided subjectively. It is highly possible that other decision makers have different preferences of the criteria weight and the normalization way. For example, during testing, some players tried to ship all the orders without thinking about the cost.

To further evaluate the implementation effects of the IA framework and prove IA's practical value, an implementation in real business environment is required. After all, the serious game is only simplified business case. The designed scenarios can be quite different from the real situation, for example, the short decision time 30 seconds per day. Since most of problems in reality are far more complex than in the game, there is a need to investigate the extent of IA's benefits in improving decision making on a real business problem, and to test how the proposed IA framework works in applying IA to reality.

6.4. Future research

On the one hand, the IA framework can be further improved by including specific tools, strategies or methods in each step. By doing so, the proposed IA framework can become a comprehensive reference that provides decision makers with more distinct instructions and assists in creating an effective human-intelligent collaboration framework. To reduce the subjective effects, the IA framework can be improved by collecting the expert opinions.

On the other hand, although the testing results in this thesis highly indicate the positive impact of applying the intelligence amplification, additional tests are needed to fully evaluate the benefits of IA in improving decision making. The additional tests are preferably in real-case business scenarios, such as the daily planning of synchromodal transport. Besides, the additional tests that include more intelligent agents are also required for testing the effectiveness of the proposed IA framework on full scale.

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Appendix

Scenario 1 for Urgent order identifier:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
No.0 De-Sout Train Mon Tue 12 Ben	No.2 De-North Train Mon Tue 6 Ben	No.4 De-North Train Tue Wed 8 Ben	No.6 De-Sout Barge Wed Thu 8 Ben	No.8 South Train Fri Fri 7 Ben		
No.1 De-south Train Mon Mon 6 Ben	No.3 North Barge Thu Fri 10 Ben	No.5 South Barge Wed Thu 11 Ben	No.7 De-Sout Barge Sat Sun 14 Ben	No.14 De-North Train Fri Sat 3 Jan		
No.9 De-Sout Barge Mon Tue 4 Jan	No.11 South Barge Tue Wed 6 Jan	No.12 De-North Barge Wed Thu 11 Jan	No.19 North Train Fri Sat 7 Marga	No.21 De-Sout Train Thu Fri 7 Marga		
No.10 De-Sout Train Mon Tue 9 Jan		No.13 South Barge Fri Sat 6 Jan	No.20 De-North Barge Thu Thu 8 Marga	No.22 De-North Train Sat Sun 8 Marga		
No.15 De-North Barge Mon Mon 8 Marga		No.17 North Barge Tue Wed 9 Marga				
No.16 North Train Tue Wed 5 Marga		No.18 North Barge Thu Fri 6 Marga				

Scenario 2 for Urgent order identifier:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
No.0 De-north Train Mon Mon 7 Ben	No.2 De-Sout Train Mon Tue 4 Ben	No.3 North Train Tue Wed 9 Ben	No.6 South Train Fri Sat 3 Ben	No.7 De-Sout Train Fri Sat 10 Ben	No.15 De-North Train Sat Sun 6 Jan	
No.1 De-Sout Barge Mon Tue 6 Ben	No.11 De-North Train Thu Fri 4 Jan	No.4 South Train Thu Fri 12 Ben	No.13 De-North Truck Wed Thu 4 Jan	No.8 De-Sout Barge Thu Fri 2 Ben	No.23 North Train Sat Sun 8 Marga	
No.9 De-south Barge Mon Mon 7 Jan	No.18 De-south Train Tue Tue 8 Marga	No.5 South Barge Tue Wed 8 Ben	No.21 De-North Barge Thu Thu 6 Marga	No.14 South Truck Fri Sat 5 Jan		
No.10 South Barge Tue Wed 6 Jan	No.19 De-North Barge Tue Wed 7 Marga	No.12 De-North Barge Wed Thu 12 Jan		No.22 North Barge Thu Fri 8 Marga		
No.16 North Barge Mon Tue 5 Marga		No.20 De-Sout Train Fri Sat 5 Marga				
No.17 De-North Train Thu Fri 8 Marga						

Scenario 3 for Auto assigner:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
No.0 De-South Train Mon Tue 8 Ben	No.2 North Train Tue Wed 9 Ben	No.4 North Train Wed Thu 12 Ben	No.6 South Barge Sat Sun 3 Ben	No.7 De-South Train Fri Sat 2 Ben	No.8 De-North Barge Sat Sun 10 Ben	
No.1 De-South Barge Mon Tue 6 Ben	No.3 De-North Train Tue Wed 4 Ben	No.5 South Barge Thu Fri 8 Ben	No.11 De-North Train Fri Sat 4 Jan	No.12 South Barge Fri Sat 5 Jan	No.22 North Train Sat Sun 8 Marga	
No.9 De-North Barge Tue Wed 7 Jan	No.10 De-South Barge Wed Thu 12 Jan	No.18 De-South Train Fri Sat 5 Marga	No.19 De-North Barge Fri Sat 6 Marga	No.13 De-North Barge Sat Sun 6 Jan		
No.14 De-North Barge Mon Tue 8 Marga	No.16 North Train Wed Thu 8 Marga		No.20 Direct Truck Wed Thu 4 Marga	No.21 North Barge Fri Sat 8 Marga		
No.15 North Train Mon Tue 5 Marga	No.17 De-North Barge Tue Wed 7 Marga					

Scenario 4 for Predictor:

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
No.0 De-North Train Mon Tue 4 Ben	No.1 De-Sout Train Mon Tue 7 Ben	No.11 South Barge Wed Thu 9 Jan	No.5 De-south Barge Sat Sun 7 Ben	No.6 De-North Barge Fri Sat 13 Ben	No.7 De-Sout Barge Sat Sun 10 Ben	
No.8 South truck Mon Tue 1 Jan	No.2 De-Sout Barge Wed Thu 11 Ben	No.17 South Barge Sat Sun 7 Marga	No.20 De-North Train Fri Sat 8 Marga	No.12 South Barge Fri Sat 12 Jan		
No.9 De-Noth Barge Tue Wed 3 Jan	No.3 North Train Tue Wed 8 Ben	No.18 De-Sout Train Thu Fri 9 Marga	No.21 South Train Thu Fri 5 Marga	No.13 South Train Thu Fri 7 Jan		
No.14 De-Sout Train Mon Tue 5 Marga	No.4 Direct Truck Mon Tue 2 Ben	No.19 De-North Train Sat Sun 7 Marga		No.22 De-North Barge Fri Sat 6 Marga		
No.15 North Barge Mon Mon 10 Marga	No.10 North train Mon Tue 9 Jan					
	No.16 De-North Barge Tue Wed 6 Marga					

Scenario 5 for Predictor:

Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday
No.0		No.2		No.5		No.6		No.12				
De-North	Train	De-Sout	Train	De-North	Barge	De-south	Barge	South	Barge			
Mon	Tue	Mon	Tue	Wed	Sat	Sat	Sun	Fri	Sat			
4	Ben	7	Ben	13	Ben	7	Ben	12	Jan			
No.1		No.3		No.11		No.7		No.13				
De-Sout	Barge	North	Train	South	Barge	De-Sout	Barge	South	Train			
Mon	Thu	Tue	Wed	Wed	Thu	Thu	Sun	Thu	Fri			
11	Ben	8	Ben	9	Jan	10	Ben	7	Jan			
No.8		No.4		No.17		No.20		No.22				
South	truck	Direct	Truck	South	Barge	De-North	Train	De-North	Barge			
Mon	Tue	Mon	Tue	Sat	Sun	Fri	Sat	Fri	Sat			
1	Jan	2	Ben	7	Marga	8	Marga	6	Marga			
No.9		No.10		No.18		No.21						
De-Noth	Barge	North	train	De-Sout	Train	South	Train					
Tue	Wed	Mon	Tue	Thu	Fri	Thu	Fri					
3	Jan	9	Jan	9	Marga	5	Marga					
No.14		No.16		No.19								
De-Sout	Train	De-North	Barge	De-North	Train							
Mon	Tue	Tue	Wed	Sat	Sun							
5	Marga	6	Marga	7	Marga							
No.15												
North	Barge											
Mon	Mon											
10	Marga											

Scenario 6 for final testing-Round 1 & Round 3

Booking	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday
	No.0	47	No.2	49	No.3	50	No.5	52	No.6	53	No.7	54	
	De-north	Train	De-Sout	Train	South	Barge	South	Barge	De-Sout	Brage	De-North	Train	
	Mon	Mon	Mon	Tue	Tue	Wed	Thu	Fri	Sat	Sun	Sat	Sun	
	7	Ben	4	Ben	8	Ben	2	Ben	10	Ben	6	Ben	
	No.1	48	No.10	57	No.4	51	No.12	59	No.13	60	No.14	61	
	De-Sout	Barge	De-North	Train	De-North	Barge	South	Barge	South	Truck	De-North	Truck	
	Mon	Tue	Thu	Fri	Wed	Thu	Sat	Sun	Fri	Sat	Sat	Sat	
	6	Ben	4	Jan	12	Ben	3	Jan	5	Jan	4	Jan	
	No.8	55	No.17	64	No.11	58	No.21	68	No.22	69	No.23	70	
	South	Barge	De-south	Train	De-Sout	Train	De-North	Barge	North	Barge	North	Train	
	Tue	Wed	Tue	Tue	Fri	Sat	Thu	Thu	Thu	Fri	Sat	Sun	
	6	Jan	8	Marga	5	Jan	6	Marga	8	Marga	8	Marga	
	No.9	56	No.18	65	No.19	66							
	De-south	Truck	De-North	Barge	North	Train							
	Mon	Mon	Tue	Wed	Tue	Wed							
	7	Jan	7	Marga	9	Marga							
	No.15	62			No.20	67							
	North	Barge			De-south	Barge							
	Mon	Tue			Thu	Fri							
	5	Marga			12	Marga							
	No.16	63											
	De-North	Train											
	Thu	Fri											
	8	Marga											

Scenario 7 for final testing-Round 2 & Round 4

Booking	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday	Sunday
	No.24	71	No.26	73	No.27	74	No.28	75	No.31	78		
	De-North	Barge	North	Barge	De-North	Train	South	Train	De-south	Train		
	Mon	Mon	Thu	Fri	Wed	Thu	Wed	Thu	Fri	Fri		
	8	Ben	10	Ben	10	Ben	5	Ben	7	Ben		
	No.25	72	No.34	81	No.35	82	No.29	76	No.37	84		
	North	Train	De-south	Barge	De-North	Barge	De-North	Train	De-North	Train		
	Tue	Wed	Tue	Wed	Tue	Wed	Sat	Sun	Fri	Sat		
	5	Ben	6	Jan	6	Jan	8	Ben	3	Jan		
	No.32	79	No.40	87	No.41	88	No.30	77	No.45	92		
	De-North	Train	De-North	Train	De-North	Barge	De-south	Barge	North	Train		
	Mon	Tue	Mon	Tue	Tue	Wed	Fri	Sat	Fri	Sat		
	6	Jan	6	Marga	9	Marga	14	Ben	7	Marga		
	No.33	80			No.42	89	No.36	83	No.46	93		
	De-Sout	Barge			De-North	Train	De-south	Barge	De-Sout	Train		
	Mon	Tue			Sat	Sun	Fri	Sat	Thu	Fri		
	5	Jan			6	Marga	6	Jan	7	Marga		
	No.38	85			No.43	90	No.44	91				
	South	Train			South	Barge	De-North	Barge				
	Mon	Tue			Wed	Thu	Thu	Thu				
	7	Marga			11	Marga	8	Marga				
	No.39	86										
	De-south	Train										
	Mon	Mon										
	6	Marga										