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Investigating Key Factors Influencing the Intention of onboard drone adoption in maritime operations: A Refined Application of the Unified Theory of Acceptance and Use of Technology (UTAUT) Model

By

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Acknowledgments

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Abstract

The quick development and integration of Internet of Things (IoT) devices onboard has prompted information systems researchers to uncover various criteria across a range of adoption models that define sailors' acceptance of such devices. Therefore, the purpose of this research is to explore the factors that affect the behavioral intentions of onboard drone adoption for maritime operations from the perspective of seafarers and manager operators of shipping businesses.

The cross-sectional study conducted applied the Unified Theory of Acceptance and Use of Technology (UTAUT) model with Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention to Use, Age, and Experience variables. This quantitative research used a questionnaire as the data collection tool with 110 respondents mostly sailors and maritime operation managers, having participated in an online survey to test the conceptual model including six hypotheses. The data derived were analyzed through structural equation modeling (SEM) by employing the PLS-SEM algorithm, the bootstrapping method, and the PLSpredict tool approaches with SmartPLS software by Ringle et al. (2022).

The results revealed that all the main constructs of the proposed model significantly and positively influenced behavioral intention with the effort expectancy (EE) having the strongest influence followed by the performance expectancy (PE) which is an outcome that comes in line with the research papers that have implemented the UTAUT model to examine the IT adoption. Unsurprisingly, none of the moderators of the model, age (A), or experience (E) could significantly moderate any of the relationships that had an impact on, according to the model.

The results of onboard drone adoption analysis can help managers and maritime sector decision-makers prioritize their actions such as training programs, organizational infrastructure, and educational programs. In the context of onboard drone use in maritime operations, this study is the first attempt to investigate experimentally the relationship between behavioral intentions and the UTAUT core components adding a great deal of theoretical value to the body of literature and simultaneously contributing to the academic community.

Keywords: technology adoption, drones onboard, maritime operations, UTAUT model, effort expectancy, performance expectancy, behavioral intentions

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List of abbreviations

UAV……Unmanned aerial vehicle

UAS……Unmanned aerial system

FSC……Fuel sulfur content

BVLOS..Beyond visual line of sight

BI……...Behavioral intention

A………Age

E………Experience

UTAUT..Unified theory of acceptance and use of technology

DOI……Diffusion of innovation

TAM…...Technology acceptance model

IT………Information Technology

IS………Information System

SEM…..Structural equation modeling

IoT……..Internet of things

AGV……Autonomous Guided Vehicles

AI……….Artificial Intelligence

IMO……..International Maritime Organization

MASS…..Maritime Autonomous Surface Ships

GPS…….Global Positioning System

EMSA…..European Maritime Safety Agency

SOLAS…Safety of Life at Sea

STCW…..Standards of Training, Certification, and Watchkeeping for Seafarers

MARPOL..International Convention for the Prevention of Pollution from Ships

MLC……..Maritime Labor Convention

SAR……..Search and Rescue

ECA……..Emission control area

TRA……..Theory of Reasoned Action

PU……….Perceived Usefulness

PEOU……Perceived Ease of Use

TPB………Theory of Planned Behavior

IDT………..Innovation Diffusion Theory

MPCU…….Model of PC Utilization

MM………..Motivational Model

PE…………Performance Expectancy

EE…………Effort Expectancy

SI…………..Social Influence

FC………….Facilitating Conditions

UB………….Use of Behavior

EFA………...Exploratory Factor Analysis

CFA…………Confirmatory Factor Analysis

CA………….Cronbach's alpha

CR………….Composite Reliability

rho_a……….Reliability Coefficient

AVE…………Average Variance Extracted

1 Chapter- Introduction

1.1 Background

Technology apart from just being crucial to the evolution of modern society, in some ways, it can be said that it is an element that distinguishes humans from even our nearest hominid ancestors (Tao & Oliver, 2020). Ever since technology arrived and invaded human life, it has changed every aspect of people's existence, playing a crucial role in developing the modern world and meeting the changing needs of humans as it has intertwined totally with societies (Simplilearn, 2023). The profound effects that technological advancements are having in fields like artificial intelligence, robotics, automation, and connected devices, as well as the opportunities and threats they are posing, have been realized by a wide range of business and commerce industries, like the maritime industry with significant technological innovations in its scope being apparent (Sinay, 2023).

Seafaring has contributed significantly to human evolution and the economic growth of every nation being transformed from a means of simply delivering food to a highly developed and quick-paced enterprise nowadays (Donepudi, 2014). Many goods are now produced in nations with less expensive resources and are shipped worldwide in wider ships such as bulk carriers, container ships, or tankers which can carry masses of cargo across the ocean than ships from the past (WOR 7, 2021). Data reveals that more than 2,500 ports worldwide service more than 50,000 professional commercial ships and thousands of smaller boats, which employ more than 2 million people worldwide, making this industry the backbone of the global economy (Donepudi, 2014). For the maritime industry to be prioritized for support and put on the urgent agendas of national governments and regulators its needs and goals must be outspoken (ICS, 2023). The shipping industry has been under pressure to accept a stronger technology push and transformation for the import and export process to be seamless and quick due to the required specialized skills and efforts, such as operating specialized machinery, in conjunction with the successful collaboration with other stakeholders involved in the process of cargo conveyance (Donepudi, 2014).

Unmanned aerial vehicle (UAV), unmanned aerial system (UAS), or remotely piloted aerial systems (RPAS) are all frequent terms used to describe **drones**, which are defined as aircraft controlled without a pilot on board (HARVARD.EDU, 2023). It is either an autonomous aircraft, with onboard computers controlling its flight, or a remotely piloted aircraft, with a pilot controlling it from a location on the ground or perhaps from another vehicle able each time to accomplish missions of a highly difficult level (Cracknell, 2017). Today, they are a growing component of the maritime industry and are used in a variety of civil, military, and government applications such as guarding the border (Laghari et al., 2023).

Drones are used extensively for a wide range of applications that support numerous scientific fields. These include infrastructure measurements of rail tracks, buildings, and bridges; construction progress and condition inspections (Wanninger et al., 2020); and pollution forensics, which involves the assessment of debris quantity, type, and distribution (Song et al., 2022). Drones are also used in the scientific field of aerospace, where they are used to exploit high-tech technologies like flight control technology (Ross et al., 2021); sensor devices, and computer vision (Shen et al., 2023); aerial photography, map surveying and mapping, forest fire prevention, wire laying, modern agriculture, and aerial monitoring (Shen et al., 2023); iceberg research (McGill et al., 2011), and maintenance purposes like spray painting exterior ship panels using UAV intelligent spray painting systems (UAV-ISP) (Cai et al., 2021).

Currently, the marine industry is utilizing UAV technology in many different areas such as maritime activity surveillance, reconnaissance missions, search and rescue operations (Cho et al., 2022); ship traffic monitoring, ship characteristics identification, illegal activity surveillance such as illegal fishing, illegal refugee, identification of drug trafficking, and human trafficking (Vella, 2020); marine pollution (Dahana & Gurning, 2020), anti-piracy activity (Zhang et al., 2018). Another area of using drones in the shipping sector is related to many kinds of gas emission detection above the ship (Hu et al., 2023); vessel inspections in Emission Control Areas (ECAs) (Xia et al., 2019); vertical air pollutant concentration control (Anand et al., 2020); concentration relationship monitoring of SO2 and CO2 in the exhaust plume of the ship (Deng et al., 2022b); NOx and SOx Emission Operational Monitoring visually or with a sniffer device (Zhou et al., 2022); efficient and quick fuel sulfur content (FSC) monitoring (Zhou et al., 2019).

Additionally, drones are also deployed in the inspections and surveys domain primarily carried out in cargo holds, ballast tanks of ships, and structural elements of offshore installations (Forsman, 2019); or even in ship hulls (Grippa, 2022). Delivery from shore to ship is a third maritime use for unmanned aerial vehicles (UAVs) that helps shipmasters receive daily deliveries of money, essential supplies, and medical equipment around the world (Forsman, 2019). Furthermore, they have been used for maintenance tasks such as spray-painting exterior ship panels with UAV intelligent spray-painting systems (UAV-ISP) (Cai et al., 2021) and iceberg research (McGill et al., 2011). Their use of UAVs in place of conventional launch boats significantly drops delivery costs, numerous injury hazards disappear, and the environmental impact is lessened (Forsman, 2019).

The desk research methodology carried out, considering reports, articles, and previous studies, demonstrated that drones are already beneficial or are expected to be useful for a variety of reasons in the future as well (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018) taking part in very difficult tasks with a higher level of autonomy, the so-called, “dull, dirty, or dangerous” missions. Although drones are being utilized more frequently in and around harbors as well as in the open oceans, in general, they are still considered novelties with their current main applications being restricted mainly to inspection and surveillance tasks (Krystosik-Gromadzińska, 2021). For this reason, the use of drones in offshore environments consists of one of the components of the future roadmap (Krystosik-Gromadzińska, 2021). A small taste of why UAV use is still limited in maritime operations at sea is theorized below.

The hazardous offshore environment sets significant demands on the drone pilots' abilities and the drones' technology, especially, the drones' payload which must be developed to withstand the effects of turbulence, strong winds, and the saltwater ocean. (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018; Krystosik-Gromadzińska, 2021). Nowadays, beyond visual line of sight (BVLOS) and autonomous flight limits, prevent drones from being completely integrated into the business since regulations in the European Union are still being drafted to support drone operations in the marine sector. (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). For instance, during exhaust plume inspections, it is necessary to fly the drone from a chase ship to get close enough to the ship under inspection because there are no regulations governing drone operation. (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). The operator's ability to extend their eyes, ears, and situational awareness at a greater distance to make the right command judgments becomes the key technical difficulty and that is why the operator's safety flight performance depends on the electronic command and control link, visual telemetry, navigation, communications, and overall mission feedback (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Contemporary onboard systems’ inability to identify the conflict in time increases the likelihood of colliding with low-flying manned aviation aircraft (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). The small drone size and extremely low altitude flight zone make it impossible for air surveillance radar to identify an air–to–air confrontation and warn the manned pilot or ground controller in time (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018).

The constant advancements taking place such as battery life extension relating to drone system range, drone communications and navigation systems development, on and off-board data analysis emerging process, fail-safe systems involvement, airspace integration, sense-and-avoid, automation technologies will lead the drone industry to get a lot closer to offering less expensive, more adaptable, and safer alternatives than the existing manned helicopter and fixed-wing aircraft (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018; Krystosik-Gromadzińska, 2021). Although drones are already employed to aid in maritime search and rescue operations, or even to identify people who may be in trouble, they are not yet able to deliver valuable cargo in terms of its weight (e.g., heavy cargo) and capacity (e.g., large cargo) (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Drones that can potentially operate over a range of 5 to 100 kilometers offshore must have reasonable access to the main shipping lanes and marine traffic centers. Radio communications for control and command over great distances provide a significant obstacle to obtaining this range. Additionally, the requirement for BVLOS distance coupled with the low flight altitude for this type of mission presents a challenge for maintaining strong radio communications despite the curving of the Earth (Deng et al., 2022c; Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Additionally, drones need to be able to stay in the air long enough to travel long distances across the maritime lanes, something which they are not able yet to achieve, whereas helicopters, while expensive, offer a high output. Therefore, drones need to increase their operational flight time endurance to compete with other aerial options. (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018).

1.2 Research Objectives

The capabilities of drones for tasks in maritime contexts already mentioned before are amazing. Although drones are not extensively used for tasks in maritime contexts over open ocean their potential for multiple purposes in such offshore contexts is anticipated to be quite promising in the future. Therefore, this research aims to explore the factors that affect the behavioral intentions (BI) of onboard drone adoption for maritime operations from the perspective of seafarers and manager operators of shipping businesses. The moderating roles of age (A) and experience (E) are also investigated to fully comprehend whether the intents of use can be influenced by exogenous variables. To achieve this, it was necessary to assess the effects of technology-related aspects on onboard drone adoption using the unified theory of acceptance and use of technology (UTAUT) model developed by Venkatesh et al. (2003) as a theoretical foundation. Hence, the primary research question to investigate the extent to which each main key factor of the theoretical model impacts seafarers' attitudes regarding the introduction of drones onboard is:

"Which was the most influential determinant of behavioral intentions to use UAV technology?"

To adequately respond to the main research question, the following secondary sub-research questions are also addressed:

(1) To what extent do other factors of the conceptual model determine the behavioral intention of shipping companies to employ drones on board during maritime operations?
(2) How do age and experience moderate the effects of effort expectancy and facilitating conditions on the behavioral intention of onboard drone use in Maritime Operations? Is there any explanation for this?
(3) Can management in maritime industries successfully foster the implementation of onboard drones, and what strategies should they employ to facilitate this innovative introduction within the fleets of merchant navy companies?

1.3 Relevance

The effort of the maritime industry to adapt to an environment where digitalization and automation are present, especially, with the appearance and establishment of drones as a useful part of seafarers during their operations at sea is of great importance (DNV, 2023). In a variety of adoption models, research on information systems has revealed many variables that affect the intentions to adopt technology proving how well-received they are (Abbad, 2021). This study examines sailors' intentions to adopt onboard drones in Maritime Operations using the unified theory of acceptance and use of technology (UTAUT), which incorporates factors across eight models. All the primary predictors listed in the original Venkatesh et al. (2003) research version were used in this study, except for usage behavior, which was not included in the investigation's purview. For the moderators, only age and experience were considered, excluding gender and willingness to use.

Several relevant studies used corresponding theoretical models, most of which had been modified by the authors themselves, by combining different models, adding, or deleting elements from specific models, or conceptualizing their constructs. Thus, the model of mobile payment systems adoption study developed by Aydın and Burnaz (2016) incorporates constructs from fifteen theories in addition to one that the authors created. Rahmaningtyas et al. (2020) research on the acceptance and use of e-learning systems creates a model based on Venkatesh et al.'s (2003) excluding all the moderator factors of the initial theoretical model. The food drone delivery investigation by Yoo et al. (2018) combines components of the technology acceptance model (TAM) and the diffusion of innovation (DOI) theories thus connecting perceptions of innovation and users' technology adoption characteristics. In this regard, the UTAUT theory of Venkatesh et al. (2003) served as inspiration for the model expansions of Martins et al. (2014), Baptista and Oliveira (2015), and Chao (2019), who added new constructs to their study conceptual models.

Specifically, in the first study, the perceived risk main construct was added and divided into other seven types of risks, namely, performance risk, financial risk, time risk, psychological risk, social risk, privacy risk, and overall risk constructs. In the second study, in addition to the four main constructs the hedonic motivation, the price value, and the habit constructs are incorporated. Furthermore, the cultural moderators of Hofstede (1980) such as individualism/collectivism, uncertainty avoidance, long/short term, masculinity/femininity, and power distance take the place of the four original motivators of the UTAUT model. For Chao et al. (2019) to examine university students' behavioral intentions toward using m-learning in higher education, they expanded the UTAUT model to include the constructs of mobile self-efficacy and perceived enjoyment in addition to satisfaction, trust, and perceived risk which consist of the security-related constructs. On the other hand, many types of research have been conducted with models like this study in terms of simplicity. More precisely, both De Sena Abrahão et al. (2016) and Puspitasari et al. (2019) studies did not use the usage behavior main construct as well as fewer moderators than the prototype model of UTAUT theory, the former did not use any moderators whereas the latter integrated only gender and age thereby looking like closer to this research. Finally, Abbad (2021) used the same main constructs as the original model without any moderator included.

"Information technology (IT) adoption including adoption models and frameworks used to investigate factors influencing a particular technology's intention to use is a very common topic in information technology (IT)/information system (IS) literature" (Martins et al., 2014). Likewise, this study's model offers a framework that clarifies the acceptance of IT and ISs. Specifically, it is about a theoretical basis that evaluates the influences of technology-related factors (i.e. drones) in the maritime industry. Although the implementation of drones in a variety of individual and organizational contexts has been one of the main focal points in many studies, few studies have referred to the specific application of drones in maritime business concepts. This indicates the theoretical significance of the study, adds to the body of literature, and provides a useful point of reference for future research. Granted that the study evaluates the maritime market's response mainly consisting of seafarers and manager operators of shipping companies before potentially launching the suggested service, it contributes to the advancement of knowledge of behavioral intention among seafarers toward onboard drone adoption. Moreover, the study presents empirical data on how external influences affect performance and effort expectancies, facilitating conditions and social impact which in turn affect behavioral intentions and show whether there is any variable that can moderate any relationship between those expectancies, conditions, and impact toward behavioral intention. Lastly, the study provides managers of marine businesses with a tool for choosing future development paths and strategies for the use of drones.

1.4 Research Design and Methodology

This study is designed to examine seafarers' and maritime business manager operators' perceptions of onboard drone adoption using as a basis the UTAUT model. The behavioral intentions for drone technology adoption will be assessed through the hypothesized relationships between the variables of the conceptual framework. The relationships among the constructs (arrows) in the model represent the research hypotheses. Empirical data was collected using a cross-sectional survey. A total of 110 questionnaires were collected and prescreened based on the respondents' onboard drone technology use intentions. After data screening, the same number of questionnaires remained for formal data analysis consisting of the measurement and structural model evaluation. The technique used for estimating the relationships that have been developed in the model is structural equation modeling (SEM). For this study, the software SmartPLS by Ringle et al. (2022) is used. More analytically, in the part of the measurement model evaluation, the PLS-SEM algorithm method was chosen to assess the indicator and the internal consistency reliability followed by the convergent and discriminant validity. In the structural model assessment, the most important procedure taking place is the hypotheses testing which uses the bootstrapping method to be accomplished. Before the hypotheses testing, multicollinearity needs also to be assessed using the PLS-SEM algorithm as well as during the model's explanatory power assessment. For the last phase of structural model evaluation, the predictive power assessment is done by the PLSpredict tool of SmartPLS software.

1.5 Thesis Structure

The thesis comprises seven chapters, i.e., Chapter 1 – Introduction, Chapter 2 – Literature Review, Chapter 3 – Research Methodology, Chapter 4 – Data Analysis and Results, Chapter 5 – Discussion and Implications, Chapter 6 – Limitations and Future Research, Chapter 7 - Conclusion

The remainder of the paper is structured as follows: Chapter 2 begins with the theoretical background; Firstly, the topic of the adoption of new technologies in the new era of the maritime world is outlined. Following this, an extended reference to the types of drones, their capabilities, and applications in the modern shipping world along with their contribution to the standardization of many maritime procedures are reported. International Maritime Regulations and the lack of those in drone handling are also addressed. The literature review ends with the TAM (Technology Acceptance Model) theory and the revised version of the UTAUT (Unified Theory of Acceptance And Use Of Technology) theory which is going to be the **key element** of the research methodology of this study; Chapter 3 outlines and goes into detail about the quantitative methodological technique used in the study, the conceptual framework, hypotheses development, variables used, the sampling and survey procedure, data collection and screening; Chapter 4 is devoted to data analysis and results presentation through the measurement and structural model evaluation; Chapter 5 makes a discussion summarizing the main findings and results of the research including implications for theory and practice; Chapter 6 presents the limitations of the study and further possible future research directions; Chapter 7 is the last chapter where the conclusions are drawn up.

2 Chapter - Literature Review

This chapter commences with drone implementation and digitalization that enhance the procedures' standardization because of the evolution of shipping operations.

Theoretical aspects of international maritime regulations are then presented, along with how UAVs have improved local and international regulations alike.

This chapter concludes with an analysis of all the technological acceptance models, including Venkatesh et al.'s (2003) UTAUT, which is a crucial component of this study's research methodological approach.

2.1 Evolution of Shipping Operations

From the invention of the steam engine during the First Industrial Revolution to the revolutionary industrial conceptions of today, Industry has undergone four technological and social revolutions (Team, 2023). The current era known as Industry 4.0-also called the Fourth Industrial Revolution or 4IR- is the next stage of digitization where the Internet of Things (IoT) and Cyber-Physical Systems (CPS) are the two major players that will also have an impact on both shipping sector and its seafarers amongst many other technologies developed as well such as Cloud Computing, Robotics and Automation, Autonomous Guided Vehicles (AGV), Virtual Reality (VR), Augmented Reality (AR), Big Data and Data Analytics, Artificial Intelligence (AI), and Additive Manufacturing, (McKinsey & Company, 2022). Contemporary Industries will be gradually moving to the future by passing a transitional stage via a retrofitting procedure of the present which is the progressive enhancement of current systems with new features or technologies (Sima et al., 2020).

The way Industry 3.0 is evolving into Industry 4.0 through digitalization, likewise, the maritime sector is adopting Industry 4.0 by implementing new technologies that have been digitalized to varying degrees shaping the future of seafaring (Shahbakhsh et al., 2022). A variety of issues including social, economic, climatic change, and, most significantly, the rapid speed of technological advancement, must encourage the maritime business to grab the chance as an opportunity to delve into the transition process taking place (Dwivedi et al., 2022). The phase through which the shipping industry has evolved throughout the years was the passage from the steam revolution to diesel engines in Shipping Revolution 2 (Marine Digital, 2020; Shahbakhsh et al., 2022). Automation and computerized systems were developed almost half a century later, in 1970, and today, as digitalization slowly permeates the marine realm, the first indicators are already visible across the industry, including ports and shipping, as well as their operations and services. (Shahbakhsh et al., 2022; ElomatiBlogPoster, 2023; DockMaster Software, 2023).

Although many industries continue to adopt Industry 4.0's digital primary focus, the scope of which involves intelligent machines and systems to automate, exchange data, or even control one another without the need for human intervention, some others have already begun to consider the effects of Industry 5.0. One of these is the shipping industry (Javaid et al., 2022; Shahbakhsh et al., 2022). The main objective of version 5.0 is to reinstate human cognition and work in the industrial context, including and, why not, even building machine robots. The collaboration of humans and robots, in which humans provide invention and creativity while utilizing robots as intelligent systems to complete essential work, will be one of the following year's visions (Shahbakhsh et al., 2022; Adel, 2022). As a result of the placement of human beings in the epicenter of the industrial framework under Industry 5.0, and their collaboration with autonomous machines, it is essential to understand the various aspects of shipping 4.0, or autonomous and unmanned ships in the era of Industry 4.0 to be ready for the future of shipping operations which have already undergone several changes due to digitalization (Alves et al., 2023). At the same time, marine productivity has increased thanks to the usage of cutting-edge technologies such as remote monitoring and cutting-edge propulsion systems (Shahbakhsh et al., 2022).

The integration of Industry 4.0 in the maritime industry requires many changes to be made in many shipping sectors such as ship types and sizes, crew competency, traffic management, transportation routes, and International Maritime Organization (IMO) laws and regulations (Ichimura et al., 2022). Apart from the changes, collaboration and coordination are also necessary, otherwise, novel systems meant to be installed will be difficult to integrate and, consequently, the industry's digitization will go slowly. (Shahbakhsh et al., 2022).

Recent developments in digitalization, machine learning, and information technologies make it feasible to implement some of these solutions for Maritime Autonomous Surface Ships (MASS), although the IMO's Maritime Safety Committee has been holding discussions about automated ships since 1964 (EMSA, 2023). For this reason, and because shipping is a global industry, IMO's definition, "a ship capable of operating independently of human interaction to varied degrees is referred to as a MASS" is going to be employed (Shahbakhsh et al., 2022; EMSA, 2023). In more detail, the IMO categorizes the autonomy of ships in four distinct degrees. In the first degree, the vessel is directly controlled by the crew being onboard even though some automated control systems are present, whereas in the second, although there is the option of the ship being controlled from another location, the presence of seafarers onboard the ship is still necessary (Fonseca et al., 2021). In the next degree, the ship can be controlled remotely from another location with no seafarers required to be onboard. In the extreme fourth-degree case scenario coming from the future, the ship will be fully autonomously controlled by decisions taken by the ship itself (Fonseca et al., 2021).

Unsurprisingly, changes to maritime education and training systems follow industry development, considering the presence of seafarers up until a third-degree autonomous ship either onboard or onshore directing the ship remotely. Interestingly, in a fourth-degree autonomous ship, seafarers still need to be educated in terms of being digital experts in their line of work and getting insight into the job scope of Shipping 4.0 (Eason, 2020; Shahbakhsh et al., 2022). Namely, in the first stage, technology is not part of education, making its presence apparent in the second. In the third stage, social media is involved in the process of learning, whereas in the last stage, the teaching process is based either on real case studies or hypothetical scenarios (Emad & Shahbakhsh, 2022). In the same way, seafarers vary according to the era they are part of, and the navigational tool each time available, hence, Seafarer 1.0 uses basic celestial navigation executed by exploiting the stars, the sun, and the moon, whereas Seafarer 2.0 uses an advanced version of this type of navigation (Shahbakhsh et al., 2022). Seafarer 3.0 operates via an electronic and automatic navigational system whereas Seafarer 4.0, although not in operation yet, might have only the role of supervising the ship's movement by being an operator of a remotely controlled console, named Operator 4.0 or e-farer, taking advantage of the digital technology field of studies (Emad & Shahbakhsh, 2022).

Theoretically speaking, the educational and instructional materials required for the autonomous ship operations of the future include cognitive abilities, effective communication, operational and technical proficiency, STEM (Science, Technology, Engineering, Mathematics) knowledge, leadership abilities, and a working grasp of mathematics and programming (Emad & Ghosh, 2023). In the educational technology field, the typical classroom is being replaced by virtual laboratories where augmented reality and virtual reality are being taught to enhance each trainee's digital skills (Shahbakhsh et al., 2022; AlGerafi et al., 2023).

In summary, two new ideas for the shipping industry's future generation have been introduced: Shipping 5.0 and Maritime 5.0. The first notion appears to be a subset of the second, even though they both seem to be concepts that are alternatives to each other. More specifically, Shipping 5.0 contains intelligent systems with human intelligence at their foundation that have replaced the smart systems of the previous generation. In contrast, Maritime 5.0 involves the collaboration of non-human agents (intelligent agents) with seafarers/marine operators accomplishing tasks in a maritime environment with intelligent attributes where the project modeling, interdisciplinary thinking, and execution, all being incorporated within (Shahbakhsh et al., 2022; Autsadee et al., 2023). In the 5.0 era, the seafarer is an intelligent "human" in the system that controls the ship and has been educated in developing fundamental competencies such as cognitive skills, cooperation, and teamwork, with artificial intelligence (AI) under an environment with ongoing technological progress (Shahbakhsh et al., 2022).

2.2 Drone Technology in Shipping

The advancements in UAV platforms after more than a century of development and the sharp progress in their characteristics, including positioning, navigation, and control technology, forced the maritime sector to add them to their operations (Shen et al., 2023; Yuan et al., 2023). Specifically, because drones demonstrate characteristics such as simplicity in deployment, intelligence, flexibility, and mobility, as well as low cost of data collecting, they are used for marine surveillance becoming experts in this task due to high-definition data acquisition, timely and precise battlefield data, and wide range of weather-conditions flexibility attributes (Yuan et al., 2023).

The different types of disposable drones are the multirotor, the fixed-wing, the single-rotor, and the fixed-wing hybrid (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). In more detail, the multirotor, mainly used for aerial photography and video aerial inspections, is easily accessible for use and camera controlling, capable of operating in restricted areas and flying shorter-range cruises without being able to carry heavy loads (Krystosik-Gromadzińska, 2021). The fixed wing, used for aerial mapping, can participate in longer-term missions than the multi-rotor with high flight speed. In addition, the fixed wing despite being expensive, is difficult to use which means that more training and available space are needed in contrast with the single rotor used for aerial laser scanning, capable of carrying a heavier load and being less dangerous to use than the fixed wing (Yuan et al., 2023). Another version of drones, the fixed-wing hybrid, used for deliveries with a big capacity to endure when flying, cannot yet fully accomplish either hovering or forward flight operations (Krystosik-Gromadzińska, 2021).

Many classification characteristics can categorize drones into different groups such as types of navigational systems, types of communication systems, and types of sensors. As far as the navigational systems are concerned, the Inertial Navigation System (INS), the Global Positioning System (GPS), and the INS/GPS integrated navigational system are the three main UAV navigation technologies available today (Shen et al., 2023). In the communication part of a UAV, the interchange frameworks have a key role in operational flight enhancement for which radio frequency (RF) correspondences are the most promising solution and its common frequency band used is from 2.4 GHz to 5.8 GHz enabling ground control of the aerial vehicle (Laghari et al., 2023). Since UAV's services are unable to support information transmission on the IoT, the Orthogonal Frequency Division Multiplexing (OFDM) able to be activated in the network can allow two subcarriers to be split into information, otherwise, the network communication capability is enabled by Non-Orthogonal Multiple Access (NOMA) (Laghari et al., 2023). To get the right signals, apart from the sensor of the UAV being a small-sized, low-weight, and low-energy consumer the existence of RF frequency converters, filters, bi-directional devices, and high-performance antennas are also necessary (Laghari et al., 2023). Turning to UAV sensor types and starting with the RGB mainly suitable for aerial photogrammetry, its weight varies between 588 and 800 grams whereas its degree of detailed vision varies from 24.2 MP to 30.4 MP and its range ability can reach up to 700 nm (Yuan et al., 2023). Like RGB's range ability, the Multispectral sensor weight range is between 170 gr to 1.7 Kg, able to zoom in to 100 MP and to be used for water quality, vegetation mapping, and classification studies (Laghari et al., 2023). Hyperspectral has the lowest zoom ability of all the other sensors and at the same time is the heaviest (Yuan et al., 2023). However, Hyperspectral can potentially cover the biggest number of nautical miles (nm), which is 2500 nm, and can be applied for the same tasks as Multispectral does (Yuan et al., 2023). LiDAR's payload is amongst the lowest of all at 760gr with a resolution capability of 100,000 s^{-1}. Its range is comparatively high at 905 nm and can be used for 3D reconstruction, erosion studies, and digital terrain mapping (Laghari et al., 2023; Yuan et al., 2023).

In the maritime sector, drones are accomplishing tasks that humans cannot or should not take part in because either their safety or even their life is put at risk (Krystosik-Gromadzińska, 2021). UAVs can fly to varying degrees of autonomy, including autonomously or remotely controlled, namely, in the first case, they are controlled by humans from a distance whereas in the second by a program placed on its mechanical parts (Krystosik-Gromadzińska, 2021). Even though drones are still regarded as innovations in the shipping industry, they have been effectively deployed for a wide variety of purposes within this sector so far (Krystosik-Gromadzińska, 2021). Throughout this paper, there are many points that drone implementations have epigrammatically been reported since they constitute part of the composition of the thesis core. Hence, at this point, some cases of drone technology applied in shipping, beyond the usual, will be only highlighted below.

1. <u>UAV Application: satellite communication system</u>

The progress of wireless networks over the last few decades supporting user services located in urban environments and the development in the fourth and fifth generations of mobile communications have led to the interaction of mobile users and Internet-of-Things (IoT) devices (Nomikos et al., 2023). Regrettably, being developed for land-based communications, the network communications left the maritime realm unaffected by this transformation (Nomikos et al., 2023). Nevertheless, the expansion of marine activities changed the scenery of wireless communications in the shipping industry. The traditional method of testing and calibrating a ship's antennae was ineffective in determining how well a system was working (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Being important to frequently check the antenna's operation following a repair, preventative maintenance, or new installation, necessitated the process of doing a sea trial by sailing the ship around and evaluating the antenna operation in the actual world (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). This test requirement is typically neglected since it takes a long time, costs a lot of money, and takes downtime, instead, to stress test and calibrate satellite communication antennas, drones were proposed (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Serving as satellite simulators, drones can quickly and cheaply test stabilized directional antennas or antennas moving freely on a platform facing the drone's motion by receiving a signal indicating that it functions as a satellite (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018). Even when the ship is at berth, drones can similarly play the role of a satellite simulating the ship's motions (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018).

2. UAV Application: Aerial Iceberg survey

Given that the experiment was conceived and carried out by scientists who boarded the ship to examine free-drifting icebergs and their physical phenomenon of calving ice, there is little doubt that this application does not serve the shipping industry's assistance in operations at first glance. However, in the high latitudes, northern or southern, the global warming effect due to greenhouse gas concentrations which cause the permafrost in the Arctic and Antarctic to melt, might increase international maritime transport activity and open new trans-Arctic shipping routes (ClimateChangePost, 2024). The analysis concerning the forthcoming trans-Arctic shipping has shown that transporting will still be rather dangerous due to the rapid ice development and sea ice ridging in the shallow (ClimateChangePost, 2024). Therefore, the study of scientific investigation through drones has been proved of great importance in terms of the knowledge acquired of the conditions in these ice-covered areas with the phenomena of the free-drifting ice and the calving ice being apparent thanks to the UAVs' real-time video transmissions flying near the ship and recording such conditions (McGill et al., 2011). The study of the icebergs demonstrated that wave erosion at the iceberg's edges causes calving episodes and in turn, the resulting waves can easily overwhelm the deck of a neighboring ship, wiping it clean of crew and equipment and thus the safe distance the ship must maintain is a minimum separation of at least three times the height of the iceberg to operate safely (McGill et al., 2011). To date, icebergs have been detected by radar and visible light satellites turning out to be ineffective, due to radars' resolution limitations (McGill et al., 2011). Surprisingly, a solution to that was the implementation of UAVs along with payloads on them, demonstrating that they were useful tools, capable of reporting the iceberg's location for many months after the survey took place along with the computation of the ocean's surface area affected throughout time by the iceberg (McGill et al., 2011).

3. UAV Application: Intelligent spray-painting method

One of the three main technological pillars of contemporary shipbuilding is shipping spray painting (SSP). Ship service life and repair time are directly impacted by SSP quality (Cai et al., 2021). Now, wall-climbing robots, frame-track robots, and elevated vehicle robots are usually used in spray painting equipment for the inner and outer panels of the dock, presenting, however, drawbacks, including a lack of capacity to handle complex curved surfaces, complicated structure, and equipment space needs all of which can be resolved by the unmanned aerial vehicle (UAV) intelligent spray painting (UAV-ISP) technology increasing safety and efficiency while lowering cost and environmental effects when it comes to being implemented in curved surfaces of outer ship panels (Cai et al., 2021). Additionally, apart from increasing spray-painting productivity that guarantees the prompt completion of this risky job, the UAV-ISP route planning and stability control method optimize the UAV spray-painting path to shorten the spray-painting time making the spray-painting UAV's control more stable than the previous traditional painting method (Cai et al., 2021).

2.3 Digitalization: Enhancement to Standardization

Seaborne trade was vibrant and prosperous up until the 18th century, with the first international trade lines thought to have appeared in the Persian Gulf about 5,000 years ago with products being transported on wooden platforms. Since that time, ship transportation has become a global phenomenon (Shaping Shipping, 2020).

Today, more than 90% of global transport is accomplished by sea, making shipping an efficient and productive method of moving both people and products (Schnurr & Walker, 2019). Although trade is advantageous, actions taking place within ports, important for trading to be successful, are quite challenging. Several steps that vessels follow when entering and leaving ports involve the submission of documents, certifications with data on their commodities, passengers' safety, and environmental protection along with sharing information on cargoes, crews, and vessel details with authorities ashore (Shaping Shipping, 2020). More importantly, due to the nature of the seafaring profession that forces officers to make the appropriate judgment in an appropriate timeframe, access to accurate and complete data records is necessary (Shaping Shipping, 2020). The operations taking place within ports where interaction between the ship and various regulatory agencies is imperative such as freight loading, unloading, storing, and forwarding impose a high level of either ship-to-shore or ship-to-ship communications to be installed so that information and data can be interchanged between the stakeholders (Shaping Shipping, 2020; Hellenic Shipping News, 2023).

More and more shipping companies are concentrating their time, attention, and money on digitalization as technology develops and industry dynamics change. The billion tonnes of commodities that are estimated to be traded by sea annually around the world, many times taking place in extremely complicated situations that involve high volume and rates of activity, are projected to become significantly more efficient thanks to technological advancements in shipping and the entire supply chain (Shaping Shipping, 2020; OECD, 2023). Therefore, it was imperative the maritime industry switch to alternative solutions, specifically, digital technologies which have become as a result a major trend over the past ten years (Hellenic Shipping News, 2023; Marine Digital,2023).

Interestingly, this technological mobility is in parallel to the accelerating change of shipping standardization which has a significant positive impact on the process of trading, ship compliance, safety, security, logistics, and the environment (Shaping Shipping, 2020; Hellenic Shipping News, 2023). For instance, an increase in efficiency in the EU logistics sector can be translated to significant cost reductions for European industries with corresponding drops in $CO2$ emissions as well (European Commission, 2023). Additionally, emerging technology like artificial intelligence (AI) and big data is vital for enhancing the efficiency and sustainability of shipping and therefore trade facilitation and economic recovery (SINAY, 2023). It is important to note that post-COVID recovery was essentially enabled by these new technologies which were key players in allowing harmonization and hence making trading both efficient and effective through the existence of three elements: simplification, harmonization, and standards (Digital Regulation Platform, 2024).

There are many times that standardization is an issue strongly highlighted in conventions. The depicted economic growth and the poverty reduction indices, made apparent the logic behind the space given for greater harmonization and standardization in commerce procedures, taking place in a global scope (OECD, 2023). Since most traded products are transported by ships, it means that people involved in shipping and logistics tasks should have thoroughly realized the importance of standards and hence apply them to their operation (Shaping Shipping, 2020; Marine Digital, 2024). For economic growth to last throughout the years, beneficial collaborations between stakeholders should agree (Tulder, 2018). Seaborne trading entails a great number of stakeholders whose actions have a significant impact on the environment and the economy. Therefore, the standards must exist to facilitate and advance the maritime sector tasks' accomplishments, and hence, the efficiency, safety, and sustainability (i.e. carbon footprint reduction) by providing all the resources and tools required, to guarantee data continuity, stakeholder connectivity maximization, and adoption of process automation at scale (Shaping Shipping, 2020).

2.3.1 International Maritime Regulations

The principal regulatory authority in the maritime industry, the International Maritime Organization (IMO), develops international regulations that are then put into practice by regional and national organizations that also have authority over how they are applied (IMO, 2019). The European Maritime Safety Agency (EMSA), the Federal Maritime Commission (FMC) for the United States, the Maritime Safety Administration of the People's Republic of China (CMSA), and others are among them (SINAY, 2022). The number of challenges that regulations aim to address in the global shipping industry are CO2 emissions minimization, environmental, social, and governance (ESG) reminder strategy to market players including investors and customers, reinforcement of use of digital technologies such as Artificial intelligence (AI), Cloud computing, Internet of Things (IoT), Machine Learning, Software as a service (SaaS), safety and cybersecurity protection and risk assessment, operational efficiency improvement, capital investment seeking, cut costs, workforce education and training program (SINAY, 2023).

The maritime industry's four regulatory pillars are the International Convention for the Safety of Life at Sea (SOLAS), Standards of Training, Certification, and Watchkeeping for Seafarers (STCW), Prevention of Pollution from Ships (MARPOL), and Maritime Labor Convention (MLC) (MIS, 2020). In more detail, the SOLAS Convention first introduced in 1974 outlines the minimal standards for commercial ships under any flag state regarding fundamental safety considerations; the construction, equipment, and operation of the ship are covered by this agreement as well (IMO, 2019). The STCW convention adopted in 1978 specifies the minimum requirements for seafarers to sail onboard commercial ships at a global scale. The MARPOL Convention, setting guidelines for preventing marine environment pollution since 1973 due to operations or accidents, particularly oil spills, has been amended under MARPOL Annex VI enforcing a 0.5% limit on the sulfur levels in fuels used by all operating ships in 1978 (IMO, 2019; SINAY, 2022). The 2006 MLC Convention's goal is to safeguard seafarers' rights in terms of respectable living and working conditions, which must be provided by governments, ship owners, and ship operators (MLC, 2006; SINAY, 2022).

Being one of the most polluting sectors, maritime shipping is trying to reach the EU's goal of reducing greenhouse gas emissions and achieving carbon neutral footprint by 2050 through a package of legislative measures adopted with four notable measures including the European Trading System Directive, the FuelEU Maritime Regulation, the Alternative Fuels Infrastructure Regulation, the Energy Taxation Directive the intention of which is the aforementioned objective as part of the battle against climate change (European Commission, 2023).

To elaborate on this, the European Trading System is a directive that all commercial vessels flying any flag and weighing more than 5,000 GT are subject to, as of 2023. Emissions from the current ETS sectors should decrease by 61% by 2030. Only 50% of GHG emissions from ships entering or leaving Europe will be considered while the total of these from the intra-EU ships will be (SINAY, 2022; European Commission, 2023). The FuelEU Maritime initiative, which will go into effect in 2025, will hasten the decarbonization of the shipping sector (SINAY, 2022; DNV, 2023). The Energy Taxation Directive (ETD) negotiates that fuels used for intra-European travel are no longer free of taxes as of 2023 (Press Corner, 2023). However, international bunkers for extra-EU travel and alternative fuels will continue to be exempt from taxes for a ten-year term. LNG will be taxed for € 0.6 per gigajoule (GJ) whereas heavy fuel oil will be taxed at a rate of about €37 per ton (Lloyd's List Intelligence, 2022). The Alternative Fuels Infrastructure Regulation introduces obligatory infrastructure deployment goals for alternative fuels such as refueling and supply facilities on land with the biggest port for this purpose in all the EU nations having the year 2030 as a deadline to be ready, while by 2025 the availability of LNG supplies must coincide with the development of this extensive onshore network (Press Corner, 2023). Overall, the basic EU regulatory framework should encompass the use of alternative marine fuels like renewable and low-carbon ones along with sustainable propulsion and power supply technologies either being supplied with power onshore or using zero-emission technology when at berth in EU ports, otherwise, fines will be banned from EU waters (EXPLANATORY MEMORANDUM, 2021). The legislative configuration must continue changing as global trade expands and the ecological disaster worsens addressing a range of issues involving people, technology, the environment, money, security, and safety (SINAY, 2022). Even though sometimes more "local" regulations like those deriving from the EU contradict those of IMO, for instance, in the end, should be harmonized and aligned with each other (SINAY, 2022).

2.3.2 UAVs: Enhancement to Maritime Regulations

Despite being crucial for trade particularly and for the global economy in general, shipping greatly increases the number of emissions that contribute to climate change (Horizon, 2022). Indices of 2022 CO2 emissions depicted that international shipping accounted for about 2% of those types of energy-related outflow at a global scale (IEA, 2023). At the same time, and despite the 2020 dramatic reduction in 2020, international shipping sector emissions, unfortunately, increased by 5% in 2022, returning to levels seen back in 2017-18 (IEA, 2023). Since this industry is responsible for transporting about 90% of world commerce, a lot of pressure is being placed on the marine sector to quickly reduce its carbon footprint (Horizon, 2022) because, otherwise, it is anticipated to gradually increase with catastrophic effects on the environment and people's lives (Velasco-Gallego, 2016). Environmental sustainability is therefore important which is why the International Maritime Organization (IMO) has set aggressive goals to cut carbon emissions per transport work by at least 40% by 2030 and by at least 70% struggling to 80% by 2040 in comparison to 2008 levels (IMO, 2023). Hopefully, digital innovations and their application in marine operations have a huge potential to assist in achieving these goals and decarbonizing the marine sector (SINAY, 2023).

Maritime digitalization refers to the use of current and emerging digital technology to alter business processes in the maritime sector (Olatunji, 2024). The amount of data collected onboard has substantially increased because of the numerous digital techniques for checking ship systems' performance (Bureau Veritas, 2022). From hull performance such as trim optimization, and improved hull cleaning, to shipping route scheduling such as weather and transit routing, this information can then be used to optimize ships (Bureau Veritas, 2022). Higher operational efficiency results in less fuel usage, reducing emissions, and making ships more environmentally friendly.

UAVs, most known as drones, are technological advancements that have a significant impact on the transportation business. Hence, the industry must embrace UAVs to step into digitalization for an efficient, profitable, safe, and sustainable industry environment (Olatunji, 2024). Mainly, made to fly without people on board, UAVs are compact and tiny and therefore less difficult and expensive to operate than conventional airplanes (Olatunji, 2024). Drones are being used more and more for logistical and surveillance purposes, for instance, to keep an eye on boundaries since they can carry cameras being able to facilitate the swift movement of small important things across short distances, and because of the autonomous flight ability, the operator may concentrate on monitoring instead of having to do remote piloting tasks (Blog, 2024; Olatunji, 2024). To date, UAVs have been applied in many circumstances reducing a wide range of activities such as ship traffic, accidents, oil spills, ship pollutant emissions like carbon footprint, non-legal actions, for instance, border illegal activities, illegal immigration, illegal fishing, illegal drug or human trafficking, piracy, risk-time-cost of activities like ship inspections or search and rescue (SAR) tasks, virus expansion like COVID-19 case, and real-time flow management (Krystosik-Gromadzińska, 2021).

Having already mentioned above both where drones have been used so far and principal information about International Organizations, Authorities, and Agencies, reviewing how the application of UAV drones for maritime purposes positively contributes to the role of these regulatory bodies, is necessary.

To commence with, the IMO, the main regulatory body, states that CO2, SOx, and NOx make up 2.6%, 13%, and 15% (weight) of the world's annual emissions, respectively, and that 70% (weight) of ship exhaust emissions occur in waters that are less than 400 km from the coast in 2021(Hu et al., 2023). These pollutants are released by ships due to fuel consumption during shipping and berthing turning into a significant cause of environmental contamination in maritime and coastal areas because of the absence of tail gas filtering equipment placed on ships (Zhao et al., 2021). Governments and the International Maritime Organization (IMO) have focused more and more attention in recent years on shipping emissions as the main cause of environmental issues. To reduce the emission of pollutants from ships, emission control measures and regulations have been developed, including compiling a list of ship emissions, collecting fuel taxes, and acquiring low sulfur fuel subsidies creating areas that control emissions (European Commission, 2022). The emission control areas (ECA) are established port's surrounding waterway zones where ships utilize low sulfur fuel content to decrease the harm that pollutant particles affect the port city (Hu et al., 2023). Participating ECA nations will apply heavy fines and may even imprison a ship if its sulfur content exceeds the standard (Gard, 2023). The International Maritime Organization (IMO) has identified four ECAs in total, with most of them being found in industrialized nations like those in Europe and North America (IMO, 2019). The International Convention for the Prevention of Pollution from Ships (MARPOL) drafted by the IMO, as well as the existing rules of regional governments, serve as the foundation for all ECA accords and decrees relating to the use of fuel oil with Annex VI of MARPOL being one such source (MARPOL, 2019).

The case study of the Yangtze River Delta, the Pearl River Delta, and the Bohai Rim whose cities are affected by COx, SOx, and NOx pollutants are Shanghai, Guangzhou, and Beijing respectively. For this reason, ships must adhere to the present international agreements and domestic laws and regulations on pollutant emission control criteria (Hu et al., 2023). Specifically, in this case, according to IMO's Marine Environment Protection Committee (MEPC) (Xia et al., 2019), ships must not use fuel oil with (FSC) $\geq 0.5\%m/m$, where FSC means fuel sulfur content (Zhou et al., 2022). The FSC is calculated by the SO_2/CO_2 (ppm to %v/v) concentration ratio with various values of which being in ANNEX I of the Directive (EU) 2016/802 of the European Parliament and the Council (Anand et al., 2020).

Granted that in this section we aim to combine drone use along with international and domestic regulations on maritime tasks how can these be related to each other in this case of China ports? The old approach of the inspection of ships with no admissible exhaust emissions involved a visual fuel oil sample examination and subsequently a double-check of the same one initially on board and finally by a third-party inspection department (SIRE, 2019). Such a complex sampling process with a lengthy test result cycle and expensive human and equipment investment costs led the marine supervisory department to implement efficient surveillance techniques based on remote sensing measurement practices by using drone-related technology equipped with sensor devices (Hu et al., 2023). This quick and low-cost monitoring method able to successfully cover many ships was widely spread and established in such tasks in the maritime sector. In addition, the traditional way of inspection of ships by ports was problematic due to delayed regulatory efficacy, narrowed regulatory scope, and skewed monitoring procedures (Enterprises, 2023). The inadequate regulatory tools due to the lack of uniform enforcement detection procedures projected a great diversification relating to the IMO law enforcement having to do with monitoring intensity and penalties such as fines and intentions for which the domestic laws for such issues were also vague including grey areas (European Commission, 2021). The ability of drones to send the data back to the land, monitor the system in real-time, quickly lock the ships that exceed the standard, and then lock the ships that violate the standard with the help of law enforcement personnel on the shore proved that the sniffing drone technology was an effective law enforcement tool (Hu et al., 2023).

Another case study with a similar approach for the same purpose, the real-time measurement-modeling system, measures the emission factors like pollutant gases (sulfur and nitrogen oxides) and particulate matter (PM) where portable exhaust monitoring apparatuses that were deployed on many platforms including drones were conducting all-weather, all-day, and real-time ship online emission detection without necessary any staff to be present to gather and calculate the results of the FSC monitoring process (Zhou et al., 2022). After the process is accomplished, the data is initially used by local marine regulatory bodies for research findings and then sent to data centers for further analysis like the MARPOL Annex VI Compliance Monitoring Coalition increasing efficiency and safety during monitoring operations by offering details on flight approach, altitude, distance to ships, speed, plume localization, sampling attempts, weather minima, and safety recommendations (Zhou et al., 2022).

2.3.3 Current Laws and Regulations for Maritime Drones

Although the use of drones onboard ships is currently not covered by any regulations established by the IMO they are likely to be governed by local legislation, and classification societies (Rak, 2023). Drone operators must be aware of these laws and always follow them. A few key considerations to keep in mind when using marine drones are followed.

To start with, depending on the country, drones used aboard ships must be registered with local aviation authorities, and based on the goal of the ship's operation taking place, licenses or certifications might be required. Limitations concerning their use restriction have to do with some designated no-fly zone areas and maximum altitude limit permitted to fly because either the first case may violate other ships sailing or in the second case airspace safety is not ensured. In addition, drones with camera apparatus should follow regulations regarding the gathering, retention, and usage of personal data (JOUAV, 2023). To date, operational flights beyond the visual line of sight (BVLOS) are prohibited by the current local regulations and laws (Marianne Harbo Frederiksen & Mette Præst Knudsen, 2018).

2.4 Technology Acceptance Model (TAM)

The potential short-term and long-term benefits, such as enhanced performance, cost and time savings, and convenience by adopting and using information technologies either at an organizational or individual level have driven information system (IS) management research to look at people's openness to new technology (Marikyan & Papagiannidis, 2023). Although a major increase in the usage of personal computers in the 1980s, the absence of actual knowledge regarding users' reactions to the performance of the information system blocked the development of research on the adoption of personal computing that had started to increase until then (Marikyan & Papagiannidis, 2023). A long time before the TAM conception, practices like user participation in both the design and deployment of IS had tried to enhance IS-related research (Chuttur, 2009; Marikyan & Papagiannidis, 2023). Analyzing and improving system design and characteristics by practitioners failed to consider and support the validity of the measures' accuracy due to the extended subjective perception of the actual use of the information systems (Marikyan & Papagiannidis, 2023). In that direction, the Theory of Reasoned Action (TRA) was created to forecast types of attitudes that underlie behaviors in a variety of contexts (Ma & Liu, 2011). However, the TRA limitations concerning its application in the information technology field, led to the technology acceptance model development (TAM) by Fred Davis (1986) based on social psychology generally and TRA particularly which comprehends the causal linkages between users' internal beliefs, attitudes, and intentions as well as forecasts and explains the acceptance of computer technology (Chuttur, 2009). Compared to its rivals TAM was thought to be more resilient, predictive, and economical (Ma & Liu, 2011). In his initial proposal, Davis introduced the constructs as follows: perceived usefulness (PU), perceived ease of use (PEOU), and attitude toward using (Ma & Liu, 2011) whose contribution of all three elements explains the user's motivation (Davis, 1986; Chuttur, 2009). The user's attitude toward a system is according to Fred Davis (1986) the characteristic that determines whether the user would utilize or reject the system. Perceived utility and perceived ease of use were thought to be the two main factors influencing the user's attitude, with perceived usefulness being directly influenced by perceived ease of use (Amadu et al., 2018). The system design features represented by X1, X2, and X3 have a direct impact on perceived usefulness and ease of use believed to affect attitude and behavior only indirectly through perceived usefulness and perceived ease of use because they fall under the category of external variables (Davis,1986). Davis et al. (1989) published the technology acceptance model again in which the behavioral intention is introduced and determined by both the user's attitude and perception of use (Kobiruzzaman, 2023). What is more, the attitude of using is directly explained by the two key beliefs, perception of use and ease of use both having an intermediary role between external variables and intention to use (Amadu et al., 2018). Behavioral intention, which is influenced by attitudes toward using and perceived utility, has an immediate impact on how the system is used (Chuttur, 2009; Amadu et al., 2018). The TAM mainly looks at two variables, perceived usefulness, and perceived ease of use to examine people's attitudes and beliefs toward the acceptance of computer technology (Szajna, 1996). The perceived ease of use has an impact on perceived usefulness directly, along with the external factors that also affect perceived ease of use (Zaineldeenetal., 2020). As has been already mentioned the TAM consists of the external variables and variables that are called constructs and are the attitude toward behavior, the behavior intention, the actual system use, and the last two, the perception of usefulness and ease of use upon which the investigation based and are critical determining factors of system use (Zaineldeen et al., 2020; Davis, 1989). Namely, the attitude toward a behavior is the degree to which a person believes that a particular activity is either positive or negative, the behavioral intention describes a person who aspires to accomplish a task without making any promises to do it, the perception of usefulness defines the degree to which a person believes that utilizing a particular application frame would improve their effectiveness at work, and the perception of ease of use which evaluates the degree to which a person believes that using a system is simple (Zaineldeen et al., 2020). The extended technology acceptance model (ETAM/ TAM 2) by Venkatesh and Davis (2000) in their efforts to make clear the perception of usefulness determinant described two groups of constructs the social influence processes and cognitive instrumental determining factors (Kobiruzzaman, 2023). The group with social variables contains subjective norm, voluntariness, and image determinants whereas the cognitive instrumental processing set includes job relevance, output quality, result demonstrability, and perceived ease of use (Kobiruzzaman, 2023). The outcome of the proposed model either voluntary or compulsory supported that the subjective norms have no bearing on voluntary surroundings whereas on perceived usefulness and behavioral intention present a diminution (Zaineldeen et al., 2020; Kobiruzzaman, 2023). The merging of TAM2 and the notion of perceived ease of use factors that gave rise to TAM3 by Venkatesh and Bala (2008) hypothesized the perception of usefulness is affected by job relevance, image, output quality, perception of ease of use, results demonstrability with subjective norms (Zaineldeen et al., 2020). The cluster including experience, output quality, and voluntariness is known as moderators whereas the sets called anchors and adjustments affect the perception of the ease-of-use determinant (Zaineldeen et al., 2020). The anchors' assembly is composed of computer self-efficacy, perception of external control, computer anxiety, and computer playfulness whereas the adjustments group consists of the perception of enjoyment and objective usability (Kobiruzzaman, 2023).

However, in the research community's attempt to focus on the most important and useful boundaries of technology acceptance theories and models to date, including the TAM 1 and 2 models, and increase the applicability of the theory to many situations, it was necessary to adopt a unified strategy that would incorporate variables reflecting various perspectives and disciplines. This was especially the case before the extension of TAM 2 to TAM 3 (Momani, 2020; Marikyan & Papagiannidis, 2023). This new, unified theory was founded on the idea that effective decision-making against any technology and the way it is used is achieved by effective real usage behavior (Momani, 2020) integrating key factors that would predict behavioral intention and use (Marikyan & Papagiannidis, 2023). As a result, and after the extensive analyses of earlier research, specifically, on IS acceptance literature examined to identify theoretical and contextual parallels and differences among the three study streams of social psychology, IS management, and behavioral psychology's views of technological acceptance (Marikyan & Papagiannidis, 2023), the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003), emerges as one of the most developed and integrated technology acceptance theories (Momani, 2020).

The theories examined and stemmed from psychological and social studies both of which are part of behavioral studies and whose characteristics benefited the UTAUT theory were the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB) along with its decomposed version (DTPB), the Technology Acceptance Model (TAM), and its extension version (TAM 2), the combination form of TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), and the Motivational Model (MM) (Momani, 2020). **Table 2.1** contains a comparison of the characteristics of these models.

Table 2.1

"UTAUT Theory and Its Foundations: A Comparison of Contributing Theories" [Source: Adapted from Momani, 2020]

Theory	Area of Advancement	Critical Analysis	References
TRA	Social Psychology	Among the most basic understandings of human behavior without considering other variables such as fear, threat, mood, or prior experience.	Ajzen and Fishbein, 1975 1980; Ajzen, 1985, 1991; Sheppard, Hartwick, and Warshaw, 1998; Ajzen, 2002.
TPB	Social Psychology	Used for the comprehension of personal acceptance and utilization of various technologies, suggesting that behaviors are planned and not influenced by other variables affecting behavioral intention.	Ajzen, 1985, 1991; Taylor and Todd, 1995; Ajzen, 2002; Pavlou and

Theory	Area of Advancement	Critical Analysis	References
			Fygenson, 2006.
DTPB	Social Psychology	By incorporating factors from the IDT model, this theory expands to become more managerially relevant for influencing adoption and usage, and while it mirrors TPB in decomposing its constructs, it still maintains the notion that behaviors are pre-planned.	Rogers 1983; Taylor and Todd, 1995; Rogers, 2003.
TAM	IT	This model, useful for technology applications, substitutes TRA's attitude toward behavior with perceived usefulness and ease of use, but is less general than TRA and TPB, excluding TRA's subjective norms and lacking feedback on factors like integration, information completeness, and currency, as well as not specifying how expectancies affect behavior.	Triandis, 1979; Davis,1986.
TAM2	IT	This theory explains perceived usefulness and ease of use through social influence, incorporating subjective norms and tracking acceptance changes over time with increasing technology experience, yet as a TAM extension, it doesn't detail how expectancies impact behavior and falls short in predicting user behavior within cultural contexts.	Davis,1986; Karahanna et al., 1999; Venkatesh, 2000; Venkatesh and Davis, 2000.
C-TAM-TPB	IT	This approach merges the TPB model from social psychology with TAM from	Triandis,

Theory	Area of Advancement	Critical Analysis	References
		the IT field, enhancing TPB's application in technology acceptance, but it does not fully incorporate TAM constructs and overlooks the aspect of planned behaviors, while still not addressing factors like fear or threat in usage.	1979; Davis,1986; Taylor and Todd, 1995.
MPCU	IT	This theory is apt for predicting individual acceptance of various technologies and excels in understanding and explaining usage behavior with a voluntary causative, while its complexity factor incorporates computer and technology usage, indirectly affecting perceived short-term consequences.	Triandis, 1979.
IDT	Social Science	This theory is versatile in studying any type of innovation, explaining, and predicting adoption rates of innovation factors, but its generality doesn't specify how attitude affects acceptance or rejection decisions, nor does it indicate how innovation factors impact these decisions.	Rogers, 1983.
MM	Social Psychology	This theory finds widespread application in motivational studies, learning, and healthcare, and can be utilized to understand new technology adoption and use, yet it requires the integration of additional factors to become more apt for studying technology usage.	Deci and Ryan, 1985.

After reviewing earlier theories before the UTAUT model, Venkatesh et al. (2003) identified the following limitations: the theories' individual-oriented information technologies and simplicity, as opposed to their complexity and advancement (Dwivedi et al., 2017); the academic conduct of the investigations with student participants, as opposed to their completion with more accurate users, such as those working for organizations (Momani, 2020); the retroactive adoption decision to implement testing procedures by earlier theories, after considering either the acceptance or the rejection of the technology used, as opposed to having it done earlier (Venkatesh et al., 2003); and the dominance of cross-sectional analysis theories in the voluntary usage character of the testing operations, making it impractical for the results (Momani, 2020).

According to the UTAUT theoretical model, behavioral intention governs how technology is used (Venkatesh et al., 2003). The direct impact of **four** main **constructs**, including **performance expectancy**, **effort expectancy**, **social influence**, and **facilitating factors**, determines the anticipated likelihood of adopting the technology. **Age**, **gender**, **experience**, and **voluntariness of use** all act as **moderators** of the influence of predictors (Ahmad, 2014). Namely, the performance expectancy is the capability of technology to benefit users and improve performance by their expectations, the effort expectancy is the user expectations regarding the ease of use of technology, the social influence is the anticipated impact of others on the user's decision to begin and continue utilizing technology, the facilitating conditions means the minimum amount of technological and organizational infrastructure required to support the application of technology and the behavioral intention refers to the anticipation of the user's purpose to make technology-related plans and decisions (Zuiderwijk et al., 2015; Momani, 2020). As for the moderators, age affects all four of the predictors, gender influences relationships between effort expectancy, performance expectancy, and social influence, experience affects the intensity of the relationships between effort expectancy, social influence, and facilitating conditions, and voluntariness of use moderates only the relationship between social influence and behavioral intention (Marikyan & Papagiannidis, 2023). Each construct in the UTAUT shares some traits with one or more constructs of other theories that have the same context (Momani, 2020). The usefulness of technology, for instance, is represented by performance expectancy, whereas, in the TAM theory is represented by perceived usefulness, and the perceived ease of use as effort expectancy, Additionally, social influence corresponds to the subjective norm in TRA, TPB, and C-TAM-TPB theories and facilitating conditions determinant emulates the corresponding perceived behavioral control in TPB and C-TAM-TPB theories (Momani, 2020).

Generally, and as has already been mentioned, the objective of the formulation of technology acceptance theories was to forecast the behavior of anticipated users and their acceptance of adopting new technologies and their use for personal or professional purposes (Surendran, 2012). With consideration for the significant evolution that had been made in the technology acceptance theories over the years and the profound understanding of the concept of technology acceptance by this evolution, this mission could be carried out in a variety of ways depending on the factors or variables that determine the testing criteria and the scientific direction that the testing operation has been carried out through (Momani & Jamous, 2017). The theories and models of technology acceptance can thus be divided into two streams for easier comprehension of the concept of technology adoption, the development method, and the scientific field in which the theories have been developed (Momani, 2020).

The first categorization of the theories is according to their method of development. In this case, the researchers either pulled out the exact findings from earlier scientific studies to create their new ones or created their models by adopting prior theories' frameworks or patterns more methodologically (Eisenhardt, 1989, Momani, 2020). The UTAUT theory, for instance, belongs to the adoption cluster of theories of the development method classification (Momani, 2020).

The second categorization refers to the scientific field each theory belongs to, amongst the social psychology, social science, and IT fields (Momani, 2020). Human behavioral studies can be classified either in social psychology or social science groups (UAGC, 2023). More complicated study of field than the behavioral studies are the technology acceptance theories as they can be created in several scientific disciplines even though all these kinds of theories can be only classified in adopting technologies of the development method category (Alshammari & Rosli, 2020). The theories concentrated upon the behavior of technology acceptance have been developed either in psychology or sociology fields whereas those concentrated on the characteristics of systems and their impact on technology acceptance have been developed in IT, and so has UTAUT, especially at a later era of technology adoption (Momani et al., 2018). As the user acceptance test serves as a software quality tool in the realm of software engineering, correspondingly, technology acceptance testing can be considered as a stage in the overall life cycle of the software product, and even so, the constructs or determinants of any of such a conceptual model, are recognized as software quality requirements the capacity of which accounts for software quality (Gillis, 2022). Additionally, the user acceptance test is a part of the Software Requirements Validation process wherein requirements reviews, model validation, prototyping, and acceptance tests are involved. In the case of the UTAUT model, the constructs that are working for software quality requirements are usability, reliability, efficiency, and adaptability (Momani, 2020). Specifically, software usability measures how simple it is for people to interact with an information system and how well they can learn from using it, software reliability represents the idea of the facilitating conditions in the UTAUT model, whereby the facilitating conditions represent the level of users' perception that an organizational and technological infrastructure exists to support the usage of the technology, software efficiency is the UTAUT model's performance expectancy notion reflected in and which is gradually improved by using the system helping users improve their job performance, and software adaptability otherwise saying in UTAUT model as social impact, is information system’s capacity capable to be altered to employ applications others than those for which it was initially supposed to (Lin, 2013; Momani, 2020). The software quality requirements mentioned can be categorized into two groups regarding their technology adoption impact; the objective effect which determines the acceptance or denial of the technology implemented and the subjective which denotes whether the implementation of the technology satisfies or not its user (Momani, 2020).

Meanwhile, efficiency and reliability indicate the objective influence of performance expectations on behavioral intention and facilitating conditions on usage behavior, whereas, on the other side, usability and adaptability stand in for, respectively, the subjective influence on effort expectations for technology adoption and the behavioral influence of social influence on intention to embrace any technology (Chang, 2012; Momani, 2020).

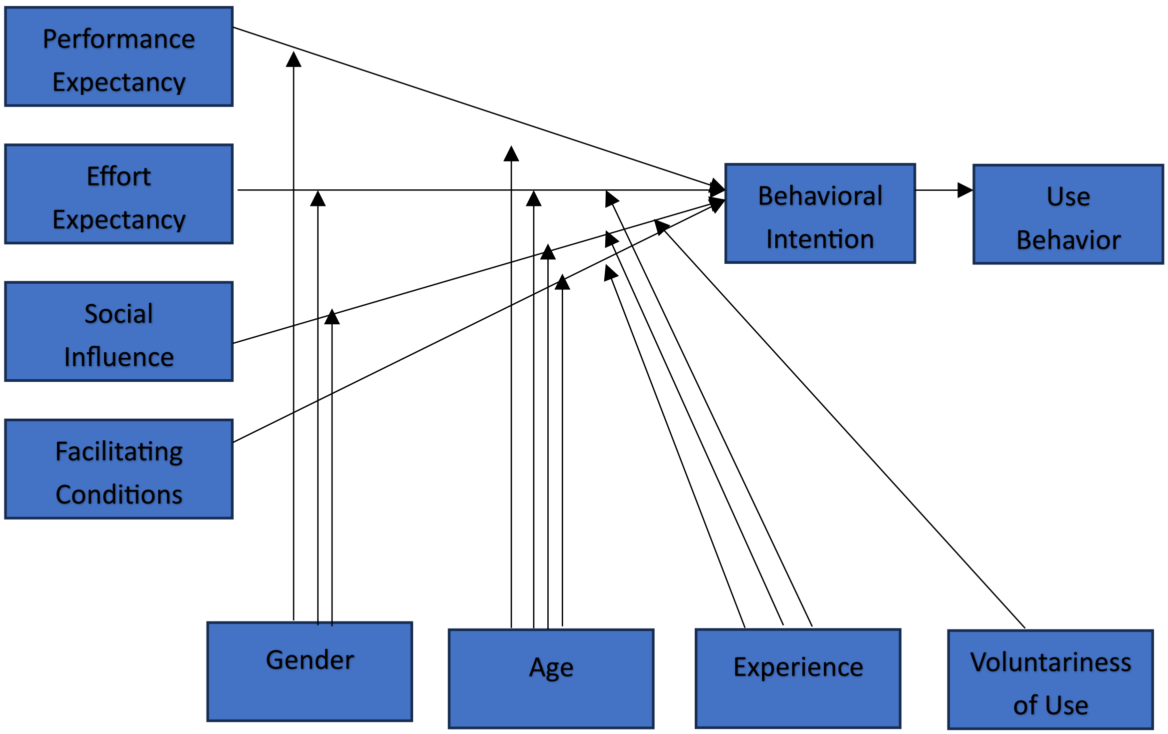

Figure 2.1 The unified theory of acceptance and use of technology (UTAUT) [Source: Venkatesh et al., (2003)]

Likewise, to the other models, UTAUT has undergone several extension operations by researchers, the most significant of which is UTAUT 2 by Venkatesh et al. (2012) (Marikyan & Papagiannidis, 2023). UTAUT 2 theory's objective was to serve as a comprehensive framework for looking at how people embrace new technologies being made to provide greater clarity when describing user behavior (Momani, 2020). The extension that took place was viewed as a consumer acceptance and use of information technology (Venkatesh et al., 2012). For the new model to fit the context of consumer technology use the researchers added hedonic motivation, price value, and habit moderated by age, gender, and experience as to being new constructs to the original first version, and hence, apart from furthering the technology acceptance literature the UTAUT model also gains an extended generalizability (Venkatesh et al., 2012). **Table 2.2** that follows provides a consolidated overview of various technology adoption models.

Table 2.2

Technology Acceptance Models: Key Characteristics [Source: Adapted from all the authors contained in the reference column of the following table]

Technology Adoption models	Key Characteristics	References
Diffusion of Innovation Theory (DOI)-1962	The Diffusion of Innovation (DoI) theory posits that the adoption of new ideas, practices, or products involves perceivable channels, time, and methods, emphasizing that this adoption is a social process driven by the dissemination of subjectively perceived information about the innovation.	Kiplang'at & Majanja, 2005; Kobiruzzaman, 2023.
Uses and Gratification Theory (U&G)-1974	The Uses and Gratifications Theory (UGT) suggests that individuals choose media based on the expected gratifications, focusing more on the consumer's choices and expectations than on the media itself or its content.	Vinney, 2022; Kobiruzzaman, 2023.
Technology Acceptance Model (TAM)-1986	The Technology Acceptance Model (TAM), developed by Davis in 1989, assesses the acceptability, adoption, and utilization of information technology using two primary constructs: perceived usefulness and ease of use. Unlike earlier models, TAM focuses not on success metrics but on investigating and predicting users' intentions to use IT, gaining substantial recognition among scholars.	Davis, 1986; Zaineldeen et al., 2020; Kobiruzzaman, 2023.
Perceived Characteristics of Innovating Theory (PCIT)-1991	The PCI theory can forecast how potential users would perceive its use because it	Yaacob & Yusoff, 2014;

Technology Adoption models	Key Characteristics	References
	doesn't just focus on the features of the innovation.	Kobiruzzaman, 2023.
The Model of PC Utilization (MPCU)-1991	The Individual Behaviors Model by Triandis (1971) led to the MPCU (Model of PC Utilization), aimed at explaining PC usage issues. This model suggests that attitudes, social norms, habits, and expected action outcomes influence behavior. MPCU focuses on factors like perceived consequences, emotions, social variables, and enabling environments, with perception outcomes including job fitness, complexity, and long-term effects. Significant factors impacting PC utilization are identified as society, complexity, job fitness, and long-term outcomes.	Jen et al., 2009; Kobiruzzaman, 2023.
Motivational Model (MM)-1992	Motivation involves encouraging individuals to perform tasks and meet goals. The Motivation Model (MM) posits that users' internal and external motivations affect their intention to use new technology. Venkatesh and Speier (1999) expanded on MM by exploring how users' attitudes toward information systems during training influence their motivations. They found that while positive moods significantly affect users' behavioral intentions and internal motivation in the short term, negative moods have a substantial impact both in the short and long term.	Jen et al., 2009; Kobiruzzaman, 2023.

Technology Adoption models	Key Characteristics	References
Motivational Model of Microcomputer Usage-1996	The study confirmed prior research on the significant role of Perceived Usefulness (PU) in promoting technology use, specifically microcomputers. It also highlighted the influence of normative social pressures and expected enjoyment as motivators for usage. The research found moderate to strong support for the proposed relationships between model variables. A key intermediary variable, perceived complexity, was identified as linking antecedent variables—skills, organizational support, and usage—with perceived utility, enjoyment, and social pressure.	Igbaria et al. 1996; Kobiruzzaman, 2023.
Extended Technology Acceptance Model (TAM 2) (ETAM)- 2002	TAM2 incorporates cognitive instrumental processing variables (like perceived ease of use, result demonstrability, output quality, and job relevance) and social influence variables (such as subjective norms, image, and voluntariness). The findings confirm that TAM2, applicable in both voluntary and mandatory settings, with subjective norms having minimal impact in voluntary contexts. Additionally, as experience increases, the influence of behavioral intention and subjective norms on perceived usefulness generally diminishes.	Zaineldeen et al., 2020; Kobiruzzaman, 2023
Unified Theory of Acceptance and Use of Technology (UTAUT)- 2003	Venkatesh et al. (2003) developed the UTAUT (Unified Theory of Acceptance	Jen et al., 2009; Kobiruzzaman, 2023.

Technology Adoption models	Key Characteristics	References
	and Use of Technology) as an integrative theory to identify additional variables affecting users' behavioral intentions, enhance explanatory power, and deepen understanding of user behavior. They found that existing models could explain only 17% to 42% of behavioral intention, with some factors diminishing in explanatory power as experience increased. The four key variables identified from past research were performance expectancy, effort expectancy, social influence, and facilitating conditions.	
Technology Acceptance Model 3 (TAM 3) - 2008	TAM3, an integration of TAM2 with determinants of perceived ease of use, focuses on key elements of both perceived usefulness and ease of use. It suggests that perceived usefulness is influenced by factors like job relevance, output quality, image, ease of use, results demonstrability, and subjective norms. Additionally, initial perceptions of a system's ease of use are shaped by 'anchors' such as computer playfulness, external control perceptions, computer self-efficacy, and computer anxiety, all related to computer usage.	Zaineldeen et al., 2020; Kobiruzzaman, 2023

Technology Adoption models	Key Characteristics	References
Extending Unified Theory of Acceptance and Use of Technology (UTAUT 2) - 2012	The theory was developed to offer a detailed framework for examining technology adoption, with the extension specifically designed to describe user behavior more accurately. A key objective was to develop a behavioral model tailored to consumer technology acceptance. To achieve this, the original model was adapted for consumer technology contexts by removing the voluntariness aspect and modifying several interactions. Additionally, three new constructs—Hedonic Motivation, Price Value, and Habit—were introduced, resulting in the creation of UTAUT2.	Marikyan et al., 2023; Kobiruzzaman, 2023

3 Chapter - Methodology

3.1 Research Model and Hypotheses Development

The research model, which was developed by using theoretically grounded hypothesized relationships between variables, is illustrated in **Figure 3.1** and describes the behavioral intents (BI) of onboard drone adoption in maritime operations. The UTAUT theory-based scales from earlier research have been employed, with appropriate item wording revisions made to fit the study's context and operationalize latent variables. Specifically, four items were created to be examined in this research for each construct of the UTAUT theory by Venkatesh et al. (2003). These items were captured by earlier research papers that used any version of TAM theory, either in its original forms such as Davis (1985), or appropriately modified for the scope of their research objectives such as Jackson et al. (2013), Martins et al. (2014), Baptista and Oliveira (2015), Aydın and Burnaz (2016), De Sena Abrahão et al. (2016), Chao (2019), Hwang et al. (2019), Abbad (2021), and Khanh et al. (2023).

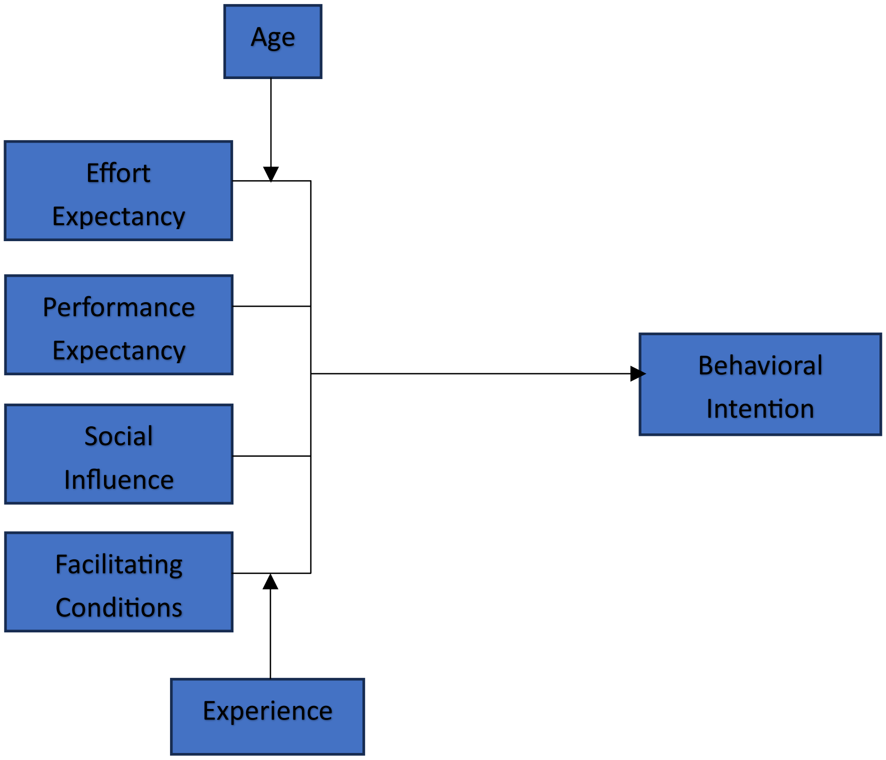

Figure 3.1 Theoretical Research Model/Conceptual Framework
[Source: Author's elaboration inspired by Venkatesh et al., 2003]
Note. This framework is the modified UTAUT model by Venkatesh et al. (2003) with two moderators out of four of those of the original model and with only two relationships moderated by these two moderators, one each.

Performance expectancy (PE) is described as "the extent to which one assumes that employing the system will help him obtain gains in job performance" (Marikyan & Papagiannidis, 2023). In other theories, performance expectancy and its related dimensions showed excellent predictive value (Momani, 2020). Additionally, the "performance expectancy" variable is significant in both voluntary and mandatory situations and is the most significant predictor of use intention, a relationship moderated by gender and age with younger males experiencing a higher influence (Momani, 2020; Marikyan & Papagiannidis, 2023). This construct is linked with the "perceived usefulness" construct of the TAM theory (Momani, 2020). According to this, a system with a high perception of perceived usefulness is one for which users think there is a good use-performance relationship where they will be rewarded by raises, promotions, bonuses, and other incentives within an organization when perform well (Davis, 1989).

H1: Performance expectations will positively influence the interest in onboard drone use in maritime operations.

Effort expectancy (EE) is analyzed as "the extent of ease related to the use of the system" (Marikyan & Papagiannidis, 2023). This construct is linked with the "perceived ease of use" construct in TAM theory (Momani, 2020) which is about “the extent to which a person thinks adopting a certain system would be effortless” (Davis, 1989). The effort expectancy construct and its related constructs in other theories significantly influence behavior intention in both voluntary and obligatory situations moderated by gender, age, and experience with a higher impact on young females and older workers in the early stages of experience (Momani, 2020). Generally, other things being equal, a user is more likely to adopt an application that they view as being simpler to use than another (Davis, 1989).

H2: Effort Expectancy will positively influence the interest in onboard drone use in maritime operations.

The **social influence (SI)** construct indicates “the extent to which a person believes that other people who are significant to them think they should utilize the new system” (Venkatesh et al., 2003). The **subjective norms**, a construct in TAM 2 theory, are like the social influence construct in that they both indicate that people's behavior is modified to how others see them (Momani, 2020). The authors noted that while the constructs related to social influence based on voluntary use were insignificant, the constructs related to social influence based on mandatory use were significant, particularly with a low level of experience and when rewards or punishment are applicable (Marikyan & Papagiannidis, 2023). Social influence manifested some similarity in its impact which was higher on older women, especially in obligatory usage during the early stages of experience and it was tempered by all the moderating variables (Momani, 2020).

H3: Social Influence will positively impact the Interest in onboard drone use in maritime operations.

Facilitating conditions (FC) construct is determined as “the extent to which one thinks that an organization and technical infrastructure exist to support the use of the system” (Marikyan & Papagiannidis, 2023). In other theories, facilitating conditions associated with constructs had the same impact on behavior intention in both usage situations, the training, and the post-training phase (Momani, 2020). Although facilitating situations have a direct favorable impact on intention to use, they are rendered unimportant by the presence of performance expectancy and effort expectancy (Marikyan & Papagiannidis, 2023; Momani, 2020). Therefore, it is expected that age and experience moderators have a greater impact on the usage of the facilitating conditions than do younger workers, especially as the experience level increases (Momani, 2020;).

H4: Facilitating conditions will positively influence the interest in onboard drone use in maritime operations.

Behavioral intentions (BI) can be characterized as the subjective likelihood that a person would engage in a particular behavior (Davis,1985). The ideas that fall under the category of behavioral intentions are the intentions of use and word-of-mouth intentions (Hwang et al., 2019). The perception of "intentions to use" encloses the extent to which a person has made intentional plans to engage in or refrain from engaging in a particular future behavior and this perception is formed after a customer's positive review (Hwang et al., 2019). The determinant of "intentions to use" has a direct impact on actual usage in many technology adoption models (Hwang et al., 2019). In addition, "word-of-mouth intentions" are described as informal face-to-face contact between a sender and a recipient about a brand name, a product, a company, or a service that is thought to be noncommercial (Hwang et al., 2019). These types of intentions coming from acquaintances are more likely to be trusted by consumers and as a result, they lower the risk associated with choosing a new good or service (Hwang et al., 2019).

Moderating role of age and experience

Age (A) affects subjective norms, attitudes, and perceived behavioral control in a manner like gender does (Momani,2020). Younger employees are better at controlling attitudes in the mandatory usage environment, while older employees are better at controlling perceived behavioral control (Momani,2020). Older workers, especially older women, are better at moderating subjective norms (Momani, 2020).

H5: Effort Expectancy which positively influences the interest in onboard drone use in maritime operations, is positively moderated by young-aged people.

The degree of **experience (E)** plays a significant role in behavior (Momani, 2020). The TRA theory and the TPB did not incorporate experience as a moderator, nevertheless, the latter, moderates the relationship between subjective norms and behavioral intention by taking into consideration that as experience levels rise, the significance of subjective standards declines (Momani, 2020). For experienced users, behavioral intention regulates the connection between the actual usage behavior of theories, such as TAM, and the perceived behavioral control (Momani, 2020). Additionally, it significantly affects how usefulness is viewed and how the activity is intended to be carried out (Momani, 2020). However, in the C-TAM-TPB theory which is a combination of the TAM theory and the TPB theory, especially for novice users, perceived behavioral control directly affects real behavior (Momani, 2020).

H6: Facilitating Conditions which positively influence the interest in onboard drone use in maritime operations, are positively moderated by people with experience in drone handling.

3.2 Variables

This paper employs the modified Unified Theory of Acceptance and Use of Technology (UTAUT) method in developing the hypotheses' formation (Yoo et al., 2018). The hypotheses are seen as a work-in-progress solution to a problem and give insight into the constructs that affect onboard drone usage (Puspitasari et al., 2019). These main constructs are Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention (Chao, 2019). According to the theory, the first four are called determining components of Behavioral Intention (Chao, 2019). The moderator variables that influence the use of drones onboard are age and experience.

In this research, independent variables, also called exogenous variables, are PE, EE, SI, and FC, whereas the dependent variable, also called endogenous variables, is only the BI. Based on the understanding that BI as a predictor of use of behavior (UB) has been extensively recognized in various user acceptability models, the influence of Behavioral Intention on Use Behavior is disregarded (Puspitasari et al., 2019).

Table 3.1

Indicators of research variables [Source: Author's elaboration]

Construct	Indicators	Items
Performance Expectancy (PE)	PE1	Performance-Enhanced Seafaring
	PE2	Rapid Tasks Completion
	PE3	Drone-Assisted Tasks
	PE4	Impossible Tasks Enabling
Effort Expectancy (EE)	EE1	Effortless Drone Usage
	EE2	Sea Tasks Easiness
	EE3	Simple Drone Interaction
	EE4	Guided Tasks Execution
Social Influence (SI)	SI1	Positive Peer Influence
	SI2	Peers Inspiring Drone Use
	SI3	Cross-Company Peer Impact
	SI4	Management-Driven Drone Adaption
Facilitating Conditions (FC)	FC1	Drone Knowledge Mastery
	FC2	Drone Support Network
	FC3	Drone Resource Availability
	FC4	Reliable Drone Maintenance
Behavioral Intentions (BI)	BI1	Drone Training Commitment
	BI2	Drone Adoption Advocating
	BI3	Onboard Drones Enthusiasm

Construct	Indicators	Items
	BI4	Drones Over Tradition
Age (A)	A1	Youthful Tech Proficiency
	A2	Youthful Tech Handling
	A3	Youthful Maintenance Crew
	A4	Youthful Learning Advantage
Experience (E)	E1	Experienced Crew's Resource Mastery
	E2	Experienced Crew's Drone Expertise
	E3	Experienced Crew's Drone Compatibility
	E4	Onboard Drone Users' Assistance

Age and experience serve as the moderator variables in this study. Based on several factors, two moderator variables from the Unified Theory of Acceptance and Use of Technology (UTAUT) method were omitted in this study. First, most of the respondents were men (97.3%) so it does not make sense for the gender moderator to be included. Although there have been significant advances in the shipbuilding and port industries (such as automated terminal technology), the field of ship operations has trailed far behind (Ghaderi, 2018). In the case of the use of drones, for instance, even though they have been successfully applied for many maritime tasks they are still considered novelties with many obstacles to overcome (Krystosik-Gromadzinska, 2021). Drones' range and capacity to carry heavy and huge loads is one of them, the advancement of which will lead to a more frequent implementation of drones in offshore regions. Hence, the voluntariness of use is the other moderator that is ignored (Krystosik-Gromadzinska, 2021). Granted that the use of drones in offshore environments is yet considered a novelty, it cannot be up to an individual seafarer whether to use or not this technology during an operational task at sea, instead, their use should be obligatory at this early phase for the shipping industry to conclude whether this kind of technology can enhance officer duties in terms of efficiency, safety, and performance.

3.3 Sampling and Survey Procedure

The research data was gathered by distributing questionnaires to seafarers and operation managers in shipping industries mainly in Greece but also the Netherlands, and students from merchant navy academies with more than a year of sea duty completion. The cross-sectional sampling procedure used in the selection of the sample continued until a total of 110 completed questionnaires had been obtained. In terms of the number of completed questionnaires, the sample size is just one over the suggested sample size of 109, which was determined using the Power Analysis method which is appropriate for SEM analysis. The G*Power statistical program 3.1.9.7, which is primarily favored by researchers in the business and social science fields, was used to perform the analysis (Memon et al., 2020). Sample sizes determined by other rules of thumb such as sample to the variable(s) ratio, sample to item(s) ratio, and sample size from the Table of Krejcie and Morgan's vary between 80 and 140 for our case scenario (Rahman, 2023) which is still a number not so diverged from that exported by the program used above.

To elaborate on the G*Power program used for our case to calculate the sample size, the users should initially determine which of the three models, namely simple, mediation, and moderation models, applies to their scenario (Memon et al., 2020). Having clarified the model, the user sets the "by default" choices applied to any case which are the "**F-tests**" method from the test family choices, the "**Linear multiple regression: fixed model, R2 deviation from zero**" from the statistical test choices, and the " **A-priori: Compute required sample size – given α, power, and effect size** " from the power analysis type options (Memon et al., 2020; Rahman, 2023). Following this, the values at 0,15 (medium effect), 0.05, and 0.80 should fill the **effect size**, **a**, and **power** input parameters accordingly (Rahman, 2023). Even though these values are recommended as suitable for social and business science research environments, the settings can be adjusted in any way that best supports each user's goals (Memon et al., 2020). The only remaining parameter that needs to be filled in, in order το export the total sample size, is the **number of predictors** which is contingent upon the study's hypothesized model, described as the greatest number of arrows in the model pointing to a dependent variable (Memon et al., 2020).

In this study, the moderation model is used. A moderating model's power is determined by its statistical model, which, in contrast to simple and mediation models, not only adds the moderator as an independent variable but also identifies the interaction terms (independent variable*moderator) of all hypothesized moderating relationships (Memon et al., 2020). As a result, it is concluded that the number "8" will be entered as the input for the number of predictors granted that in the proposed theoretical model there are four independent variables, two moderators, and two interactions of the moderators with the independent variables aggregately, one interaction with each moderator. Setting all these parameters, the G*Power shows 109 as the minimum sample size required in this research. The survey was used and launched for three months, from September to November 2023, after which the information was used to investigate the model that was suggested. The online form of the questionnaire was designed through Google Forms, a reporting platform that served as a tool to manage data such as gathering, saving, and analyzing the responses. The questionnaire which was developed in English and was based on the literature and the research model was divided into two parts. The first section contained demographic information (4 questions) collecting basic information about respondents' characteristics, including age, gender, school education, and drone-using experience. In the second section, 28 items were used to measure the seven constructs presented in the research model **(Figure 3.1)**. To quantify the constructs, a five-point Likert scale consisting of five answer options (ranging from "1" for strongly disagreeing to "5" for strongly agreeing) has been adopted to rate the questionnaire responses. The items about each construct in the proposed model and the studies that were used as a point of reference for their adaptation are compiled in **Table 3.2**. Important to mention that the readers are unable to identify the participants because the data was anonymous as the names of the respondents from shipping companies and the merchant navy schools are not provided and there are no name lists that match the questionnaire respondents. After participants of the study gave informed consent, having first been informed about the nature of the investigation, they were given the guarantee that their replies would be kept private, anonymous, and utilized exclusively for the study.

Table 3.2

Measurement scales and references of proposed constructs [Source: Author's elaboration]

Construct	Description of scale items	Source(s)
Performance Expectancy (PE)	PE1 My expectation about using drones for onboard operations at sea is that it will improve my job performance. PE2 Using drones for onboard operations at sea will enable me to accomplish an assigned task more quickly. PE3 Using drones for onboard operations at sea will support critical aspects of my job. PE4 Using drones will allow me to accomplish specific tasks that would otherwise be impossible.	Jackson et al. (2013); Martins et al. (2014); Baptista and Oliveira (2015); Aydın and Burnaz (2016); De Sena Abrahão et al. (2016); Chao (2019); Abbad (2021); Khanh et al. (2023).

Construct	Description of scale items	Source(s)
Effort Expectancy (EE)	EE1 I think I will find it easy to use drones for onboard operational tasks at sea. EE2 I will feel comfortable using drones as part of regular tasks onboard. EE3 Interacting with drones may not require a lot of my mental effort. EE4 Drones will provide helpful guidance in performing tasks.	Jackson et al. (2013); Martins et al. (2014); Baptista and Oliveira (2015); Aydın and Burnaz (2016); De Sena Abrahão et al. (2016); Chao (2019); Abbad (2021).
Social Influence (SI)	SI1 People who are important to me could influence me positively in using drones. SI2 The opinions of peers whom I work with could encourage my option of using drones. SI3 Colleagues' opinions (e.g., seafarers working on ships other than mine owned by other shipping companies) could affect me positively in using drones. SI4 Management of the ship (e.g., master of the ship/shipping operations manager) can encourage the adoption of drone technology.	Jackson et al. (2013); Martins et al. (2014); Baptista and Oliveira (2015); Aydın and Burnaz (2016); Abbad (2021).
Facilitating Conditions (FC)	FC1 I think I will have the necessary knowledge to use drones. FC2 A specific person (or group) is available for assistance with drone utilization difficulties. FC3 I think there will be the necessary resources (e.g., charging stations, operating	Martins et al. (2014); Baptista and Oliveira (2015); Aydın and Burnaz (2016);

Construct	Description of scale items	Source(s)
	manuals, etc.) available for using drones onboard. FC4 I think there will be a reliable system in place for the maintenance and repair of drones.	Abbad (2021).
Behavioral Intentions (BI)	BI1 I am willing to invest time in learning to operate drones for onboard operations. BI2 I would recommend the adoption of drone technology for onboard operations to my colleagues/ other seafarers. BI3 I am enthusiastic about the prospect of using drones in my onboard tasks. BI4 I prefer to use drones over traditional methods for tasks such as surveillance, delivery, or maintenance.	Jackson et al. (2013); Martins et al. (2014); Baptista and Oliveira (2015); Aydın and Burnaz (2016); Hwang et al. (2019); Abbad (2021); Khanh et al. (2023).
Age (A)	A1 It is easier for the younger crew to become skillful at handling the technological devices during operations on board than the older ones. A2 Handling problems related to technological/ technical devices such as drones, requires the active-perceptive approach which is typical of younger people. A3 It is preferable for the youngers on board to be allocated to maintenance and repair of technological/technical devices such as drones than the older staff.	Baptista and Oliveira (2015).

Construct	Description of scale items	Source(s)
	A4 It will be easier for youngers to acquire the knowledge required to use the updated version of the device when necessary than the older crew of the ship.	
Experience (E)	E1 The experience of the crew in handling/using drones makes it easier for them to discover the necessary resources to also use the drones in operations onboard, than for the inexperienced crew. E2 The experienced crew in handling drones may have the necessary knowledge to use drones in operations onboard. E3 The experienced crew in Drone handling find its use compatible with other similar technologies they use. E4 Onboard drone users can get help from other experienced in handling drone members of the crew when they have difficulties in using them.	Jackson et al. (2013); Baptista and Oliveira (2015).

3.4 Data Collection and Screening

Once the survey procedure has ended, it means that the data collection has been accomplished. To use the data and proceed to data analysis it needs first to enter the data either in an SPSS software program or in a Microsoft Excel spreadsheet which was finally used in this study. After the data has been keyed in the Excel spreadsheet, it should be checked for any errors, outliers, respondent misconduct, or missing data. The minimum and maximum functions, the average function, the missing value function, and the standard deviation function were employed to ensure that any of the previously listed discrepancies did not occur. After applying the minimum, maximum, and average functions, some values were detected as outliers but after checking again the questionnaire data we concluded that there were no invalid answers, instead, typographical errors only took place by the researcher that were corrected at the end. Similarly, detecting the missing values via the missing values function proved there was no failure on the respondents' side to answer any of the questions posed. The respondent misconduct was checked by applying the standard deviation function. The most common misconduct on the respondents' part occurs occasionally when a respondent simply indicates agreement at the same level throughout the survey without reading the questions. To examine if such a situation took place, we apply the standard deviation function in each row of the data worksheet. Should any standard deviation value of less than 0.25 appear, this answer may be removed from the survey since it indicates little to no variance among the responses throughout the survey (ResearchWithFawad, 2021). Across this survey, the lowest standard deviation value was 0.39 and as a result, no response was subject to deletion for respondent misconduct issues. After completing the data screening and the missing data handling procedure the sample size remained the same in number (=110) since none of the answers was deleted. Therefore, the sample size was considered adequate.

In the research sample, almost, all participants are males 97.3% (n=107), and only 2.7% (n=3) are females. The group of people from 18 to 24 accounts for 22.7% (n=25), those aged between 25 and 34 account for 39.1% (n=43), and the other from 35 to 44 consists of 23.6% (n=26). In addition, the group aged between 45 and 54 makes up 9.1% (n=10), the 55 to 64 age group makes up only 3.6% (n=4), and the over 65 age group accumulates the lowest percentage of all, 1.8% (n=2); only 7.3% (n=8) had a high school level degree or lower, those with academic qualifications of associate and bachelor's degree account for 72,8% (n=80), and 20% (n=22) with graduate degree (master or doctoral). Regarding participants' experience in drone handling which accounted for 31.8%, most of them 23.6% (n=26) stated to have a low-level experience, whereas only 8.2% (n=9) were either medium or highly-level experienced in flying them. Detailed information about the distribution of respondents' demographics is presented in **Table 3.3**.

Table 3.3

Description of respondents' demographics (n=110) [Source: Author's findings extracted by Google Forms]

Demographics	Value	n	Percentage
Gender	Male	107	97.3%
	Female	3	2.7%
Age	18-24	25	22.7%
	25-34	43	39.1%
	35-44	26	23.6%
	45-54	10	9.1%
	55-64	4	3.6%
	≥65	2	1.8%
Educational Level	≤High School Degree	8	7.3%
	Associate's degree	28	25.5%
	Bachelor's degree	52	47.3%

Demographics	Value	n	Percentage
	Graduate degree (Master/Doctoral)	22	20%
Drone Handling Experience	None	75	68.2%
	Low	26	23.6%
	Medium	7	6.4%
	High	2	1.8%

4 Chapter - Data Analysis and Results

4.1 Methods and Techniques

The structural equation model, or SEM, regarded as a set of connected statistical procedures rather than a single process, analyzes the interactions between multiple variables simultaneously (ResearchWithFawad, 2021). Between the two SEM procedure families existed which are the variance and the covariance-based methods (Baptista & Oliveira, 2015), the partial least squares (PLS) variance technique is used in this research owing to the model complexity (Martins et al., 2014; Phuthong, 2019). This practical and effective statistical method which is suitable for numerous study scenarios (Baptista & Oliveira, 2015), was executed with SmartPLS 4.0.9.6 software version (Ringle et al., 2022) used to analyze and interpret the reliability and validity of the measurement model and assess the structural model (Naser & Jiroudi, 2016). In addition, to test and evaluate the conceptual research model and the relationships among the hypothesized constructs, the PLS-SEM algorithm, bootstrapping, and PLSpredict methods were performed (Chao, 2019). During the use of this statistical software, the company released some updates reaching up to the 4.0.9.8 version until the end of this study.

4.2 Measurement Model Evaluation

The first step in assessing PLS-SEM results involves analyzing the measurement models (Martins et al., 2014). Different criteria apply to reflective and formative constructs and the different models they create (Hair et al., 2019). In the formative measurement model, the arrows are pointing from the indicators to the construct denoting a causal relationship whereas in the reflective measurement model, the arrows are inverse showing that its constructs “cause the measurement of the indicator variables” (Hair et al., 2021). Another category that constructs are divided into, is whether they are "Higher-order" or "Lower-order" constructs. The difference is that the former has many construct layers whereas the other is only one construct (Hair et al., 2021). The lower-order constructs of the reflective measurement model of the conceptual model of this study are evaluated for reliability and validity (Baptista & Oliveira, 2015; Chao, 2019). Specifically, the assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity are the steps followed consecutively in measurement model evaluation (Martins et al., 2014; Baptista & Oliveira, 2015).
Following the split of the constructs, it is crucial to discuss the techniques used to either find patterns and links in the data or validate pre-existing theories. PLS-SEM is suitable for both confirmatory and exploratory research purposes (Hair et al., 2019; Naser & Jiroudi, 2016). The exploratory factor analysis (EFA) method is applied to identify causal relationships in less-developed or still-emerging theories, whereas the confirmatory factor analysis (CFA) method is applied to test the causal relationships of existing theories and concepts (Hair et al., 2019), as a result, the confirmatory factor analysis method is carried out in this research problem.

The **first phase** in the reflective measurement model evaluation process involves the **indicator reliability** assessment through the indicator loading values by looking at the percentage of each item’s variance that can be attributed to its construct (Hair et al., 2019; Hair et al., 2021). This indicator’s variance is calculated by squaring the indicator loading, or the bivariate correlation between the indicator and the construct (Hair et al., 2021). The recommended factor loading values are those that are higher or equal to 0.708 (Martins et al., 2014; Baptista & Oliveira, 2015; Hair et al., 2021). Generally, indicators with loadings between 0.40 and 0.708 should only be removed, if doing so raises the recommended threshold value for either convergent validity or internal consistency reliability (Baptista & Oliveira, 2015; Phuthong, 2019; Hair et al., 2021). Consequently, indicators that have lower loadings are occasionally kept (Hair et al., 2021). Nonetheless, indicators with extremely low loadings (below 0.40) ought to be always removed from the measurement model (Baptista & Oliveira, 2015; Hair et al., 2021). In the literature, the term indicator loading is also alternatively referred to either as factor loading (Baptista & Oliveira, 2015), or outer loading (Hair et al., 2021) values.

Findings from the CFA indicated that 9 items namely, A1, A2, A3, EE3, E1, E3, E4, FC2, and FC3 had low factor loadings since they were below 0.708. However, because the A2, A3, EE3, E3, E4, and FC2 had factor loadings below 0.4 and according to what has already been said, these items should automatically be eliminated. After dropping these indicators out, the remaining items with low factor loading values, although they presented higher values than before, were nevertheless slightly below the 0.708 accepted value once again. However, at this point, no items will be removed further. The estimation of whether to retain the remaining items or eliminate any of them will be determined by the following measurement model evaluation outcomes that follow. Factor loadings are presented in **Table 3.4**.

Table 3.4

Factor loadings [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Items	01. PE	02. EE	03. SI	04. FC	05. A	06. E	07. BI
PE 1	0.900						
PE 2	0.866						
PE 3	0.903						
PE 4	0.743						
EE 1		0.857					
EE 2		0.868					
EE 4		0.826					
SI 1			0.792				
SI 2			0.894				
SI 3			0.891				
SI 4			0.827				
FC 1				0.808			
FC 3				0.692			
FC 4				0.727			
A1					0.695		
A4					0.966		
E1						0.675	
E2						0.935	
BI 1							0.836
BI 2							0.906
BI 3							0.936
BI 4							0.726

The **second phase** in the reflective measurement model assessment contains the **internal consistency reliability** which is known as the degree to which indicators measuring the same construct are related to one another (Phuthong, 2019; Hair et al., 2021). The two metrics used to evaluate the constructs' reliability are Cronbach's alpha (CA) and composite reliability (CR) (or as rho_c will often appear in research papers), which show how effectively a collection of manifest variables assesses a single latent construct. (Martins et al., 2014; De Sena Abrahão et al., 2016; Phuthong, 2019; Naser & Jiroudi, 2016; Chao, 2019; Hair et al., 2021). Rho_c numbers in the 0.60–0.70 range are deemed "acceptable in exploratory research," but values in the 0.70–0.90 range are deemed "satisfactory to good," and values over 0.90 and consequently above 0.95 are troublesome (Hair et al., 2021). Another indicator of internal consistency reliability that operates under the same assumptions as rho_c is CA's value whose score interpretation is comparable to that of composite reliability (Phuthong, 2019; Hair et al., 2021). The reliability coefficient (rho_a) presented in many studies is seen as a reasonable compromise between the two metrics since it typically falls between the conservative CA and the rho_c (Hair et al., 2021). **Table 3.5** displays the findings for CA and rho_c. Cronbach's Alpha ranged from 0.540 to 0.877. Specifically, three out of seven constructs had CA values below 0.70, and one of them was below 0.60 showing poor consistency reliability. However, this is not a concern for wondering about whether to eliminate any of the items that existed, granted that this would happen in the case of improving the rho_c and the AVE constructs' values from below the threshold level to the required level if that was the case (Latif et al., 2020). In this research, rho_c to the statistic values ranged from 0.787 to 0.916 which is over the required threshold of 0.70. The value of the AVE constructs' value and whether it exceeds the threshold level will be assessed in the following stage. Based on the results, it will then be decided whether to remove any items to improve their worth. In addition, the rho_c is thought to be a more accurate indicator of internal consistency than CA due to the utilization of the standardized loadings of the manifest variables (Phuthong, 2019), hence, from these two points of view, the construct reliability is established.

Table 3.5

Internal Consistency Reliability Analysis (Cronbach Alpha and Composite Reliability) [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
PE	0.877	0.901	0.916
EE	0.809	0.811	0.887
SI	0.876	0.903	0.914

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
FC	0.651	0.687	0.787
A	0.654	1.169	0.826
E	0.540	0.736	0.794
BI	0.874	0.894	0.915

Note. Rho_a, a value not mentioned in the text, does not give valuable insights into the measurement assessment procedure. However, it should always be valued between CA and CR, as is the case.

The **last stage** of the measurement model evaluation of a reflective model contains the **construct validity assessment** divided into two parts, the **convergent validity**, and the **discriminant validity** (Hair et al., 2021).

Convergent validity is known as the degree to which the construct converges to explain the variance of its indicators and the AVE for each construct's indicators is the metric used to assess a construct's convergent validity (i.e., mean square of the loadings of each indicator) (Hair et al., 2021). The AVE values higher or equal to 0.50 for all endogenous and exogenous constructs indicate convergent validity (Naser & Jiroudi, 2016). Except for the FC construct, which was marginally above the 0.50 threshold AVE value, all constructs in this study have AVE statistics above the necessary threshold of 0.50, with most of them achieving high values of over 0.70. Consequently, the results showed that convergent validity is established. Following the previous analysis on factor loading values and whether to eliminate any item, having already calculated that both convergent validity (AVE) and composite reliability of the previous stage have acquired values over their threshold required, we conclude that no item needs to be dropped out (Latif et al., 2020). **Table 3.6** demonstrates the AVE value for each of the constructs.

Table 3.6

Construct *Convergent Validity (AVE) [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]*

Construct	Average variance extracted (AVE)
PE	0.732
EE	0.723
SI	0.726
FC	0.553
A	0.708
E	0.665
BI	0.731

Discriminant validity is a metric that quantifies how different a construct is from other constructs of the structural model (Hair et al., 2021). Fornell and Larcker and cross-loading criterion are applied to evaluate the discriminant validity between constructs (Naser & Jiroudi, 2016). However, Henseler et al. (2015), concluded that due to the insufficiency of the previous metrics to assess discriminant validity, the Heterotrait-Monotrait (HTMT) ratio of correlations is necessary to be calculated additionally (Naser & Jiroudi, 2016; Hair et al., 2021).

Fornell-Larcker criterion, a traditional metric, suggests the squared variance within each construct be compared to the squared inter-construct correlation of that construct and all other reflective constructs measured in this structural model and not being more than their AVEs (Hair et al., 2021). The square root of AVE (in Bold and Italics) for a construct in this study was shown to be higher than its correlation with other constructs (**Table 3.7**), which strongly supports the idea that discriminant validity has been established.

Table 3.7

Discriminant Validity – Fornell & Larcker Criterion [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Construct	PE	EE	SI	FC	A	E	BI
PE	***0.855***						
EE	0.701	***0.851***					
SI	0.351	0.319	***0.852***				
FC	0.414	0.469	0.368	***0.744***			
A	-0.074	-0.032	-0.047	0.067	***0.842***		
E	0.097	0.098	0.101	0.128	0.261	***0.815***	
BI	0.728	0.756	0.430	0.593	0.102	0.166	***0.855***

Note. Bold and Italics represent the square root of AVE.

Cross Loadings

The loadings display how the item would load under its underlying construct as well as how it would load with the study's other constructs (ResearchWithFawad, 2022). Furthermore, an indicator's loadings on its variable are always higher than all its cross-loadings with other variables, as seen in **Table 3.8** when comparing the loadings across the columns. Therefore, based on the assessment of cross-loadings, discriminant validity is accomplished.

Table 3.8

Discriminant Validity – Cross loadings [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Construct-Items	PE	EE	SI	FC	A	E	BI
PE 1	0.900	0.737	0.339	0.439	0.003	0.071	0.752
PE 2	0.866	0.587	0.350	0.339	-0.040	0.125	0.604
PE 3	0.903	0.576	0.253	0.344	-0.128	0.084	0.607
PE 4	0.743	0.452	0.246	0.265	-0.117	0.050	0.489
EE 1	0.519	0.857	0.229	0.439	0.024	0.108	0.592
EE 2	0.538	0.868	0.289	0.400	0.035	0.090	0.679
EE 4	0.726	0.826	0.290	0.362	-0.140	0.055	0.651
SI 1	0.293	0.192	0.792	0.239	-0.119	0.024	0.239
SI 2	0.378	0.293	0.894	0.308	-0.074	0.088	0.409
SI 3	0.228	0.236	0.891	0.316	0.007	0.075	0.330
SI 4	0.285	0.326	0.827	0.363	0.001	0.129	0.430
FC 1	0.405	0.560	0.334	0.808	0.093	0.040	0.594
FC 3	0.158	0.110	0.179	0.692	0.036	0.130	0.250
FC 4	0.272	0.188	0.259	0.727	-0.008	0.171	0.350
A1	-0.049	-0.012	-0.004	-0.110	0.695	0.210	0.039
A4	-0.073	-0.035	-0.055	0.122	0.966	0.242	0.110
E1	0.035	0.130	0.036	-0.054	0.166	0.675	0.082
E2	0.105	0.062	0.110	0.187	0.249	0.935	0.170
BI 1	0.543	0.578	0.396	0.549	0.129	0.105	0.836
BI 2	0.680	0.720	0.361	0.523	0.041	0.148	0.906
BI 3	0.678	0.736	0.412	0.610	0.115	0.167	0.936
BI 4	0.582	0.526	0.295	0.310	0.064	0.147	0.726

Heterotrait-Monotrait Ratio (HTMT)

The HTMT is "the mean value of the indicator correlations across constructs (heterotrait-heteromethod correlations) concerning the geometric mean of the average correlations for the indicators measuring the same construct (the monotrait–heteromethod correlations)" (Hair et al., 2021). For structural models including conceptually quite similar constructs, the threshold value is 0.90, whereas for those that have conceptually different ones, the threshold value is 0.85 (Naser & Jiroudi, 2016; Hair et al., 2021). In this research model, the constructs are conceptually similar, as they describe user behavior (Kobiruzzaman, 2023). In addition, there is no discriminant validity problem since all the values extracted are below 0.90 as can be seen in **Table 3.9,** and hence, discriminant validity is attained.

Table 3.9

Discriminant validity- Heterotrait/Monotrait Ratio (HTMT) [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Construct	PE	EE	SI	FC	A	E	BI
PE							
EE	0.814						
SI	0.393	0.362					
FC	0.476	0.515	0.432				
A	0.123	0.122	0.110	0.213			
E	0.126	0.176	0.126	0.271	0.453		
BI	0.821	0.890	0.471	0.679	0.116	0.223	

4.3 Structural Model Evaluation and Hypotheses Testing

After confirming the validity and reliability of the construct measurement, the following step involves the structural model evaluation including the investigation of collinearity problems, the significance and relevance of the structural model relationships, and the model's explanatory and predictive power evaluation (Naser & Jiroudi, 2016; Hair et al., 2021).

The **first step** that will take place in the structural model evaluation is to examine whether **multicollinearity** is a problematic issue. Although it is a procedure comparable to evaluating formative measurement models, in this instance, the variance inflation factor (VIF) values are determined using the predictor constructs' score in each regression in the structural model because each set of predictor constructs' high correlations can skew the point estimates and standard errors (Hair et al., 2021). Although the multicollinearity critical threshold value is 5 (Phuthong, 2019), it does not mean that at lower values of 3-5, collinearity is not likely to occur (Hair et al., 2021). In our study, the VIF values extracted and displayed in **Table 3.10** are all less than 3, and hence no issue of collinearity exists.

Table 3.10

VIF values [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Constructs' Direct Relationships	VIF
01. PE -> 07. BI	2.081
02. EE -> 07. BI	2.154
03. SI -> 07. BI	1.287
04. FC -> 07. BI	1.478
05. A -> 07. BI	1.122

Constructs’ Direct Relationships	VIF
06. E -> 07. BI	1.106
06. E x 04. FC -> 07. BI	1.109
05. A x 02. EE -> 07. BI	1.130

The **second step** involves the **significance** and **relevance assessment** of the **path coefficient** of total effects, the sum of direct and indirect effects connecting one construct to another in the model (Phuthong, 2019; Hair et al., 2021). The significance assessment computes the t-values of path coefficients, or confidence intervals, using bootstrapping standard errors as a foundation, hypothesizing a path coefficient being significant at the 5% level when the value zero is outside of the 95% confidence interval. (Hair et al., 2021). Regarding relevance, path coefficients typically range from -1 (strong negative relationship) to +1 (strong positive relationship) with values either below -1 or above +1, most probably arising in cases of high levels of collinearity not being admissible (Hair et al., 2021). When one predictor construct's standard deviation unit changes, the path coefficients show the changes in an endogenous construct's values that correspond to those changes, keeping all other predictor constructs constant (Hair et al., 2021). The **first part** of **this step** starts with the **direct relationships** between variables:

H1 assesses whether PE positively influences the interest in onboard drone use in maritime operations. The results revealed that performance expectations have a positive impact on the use of drones onboard ships during operation tasks (B= 0.334, t= 4.953, p<0.05). Hence, H1 is supported.

H2 assesses whether EE positively influences the interest in onboard drone use in maritime operations. The results revealed that effort expectancy has a positive impact on the use of drones onboard ships during operation tasks (B=0.383, t=5.948, p<0.05). Hence, H2 is supported.

H3 assesses whether SI positively impacts the interest in onboard drone use in maritime operations. The results revealed that social influence has a positive impact on the use of drones onboard ships during operation tasks (B=0.128, t=2.282, p=0.011). Hence, H3 is supported.

H4 assesses whether FC positively influences the interest in onboard drone use in maritime operations. The results revealed that facilitating conditions have a positive impact on the use of drones onboard ships during operation tasks (B=0.204, t=2.927, p=0.002). Hence, H4 is supported.

The results for the hypotheses that concern the direct relationships of the structural model are presented in **Table 3.11**. The structural model is presented in **Figure 3.2** which is an exported image by SmartPLS4 (Ringle et al., 2022).

Table 3.11

Direct Relationships [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Relationships	Beta Coefficient	Standard deviation	T statistics	P values	Decision
01. PE -> 07. BI	0.334	0.068	4.953	0.000	Supported
02. EE -> 07. BI	0.383	0.064	5.948	0.000	Supported
03. SI -> 07. BI	0.128	0.056	2.282	0.011	Supported
04. FC -> 07. BI	0.204	0.070	2.927	0.002	Supported

Note. B= Beta Coefficient, SE= Standard Error, T= t-statistics, P= Probability (P) value. *Relationships are significant at $p<0.05$.

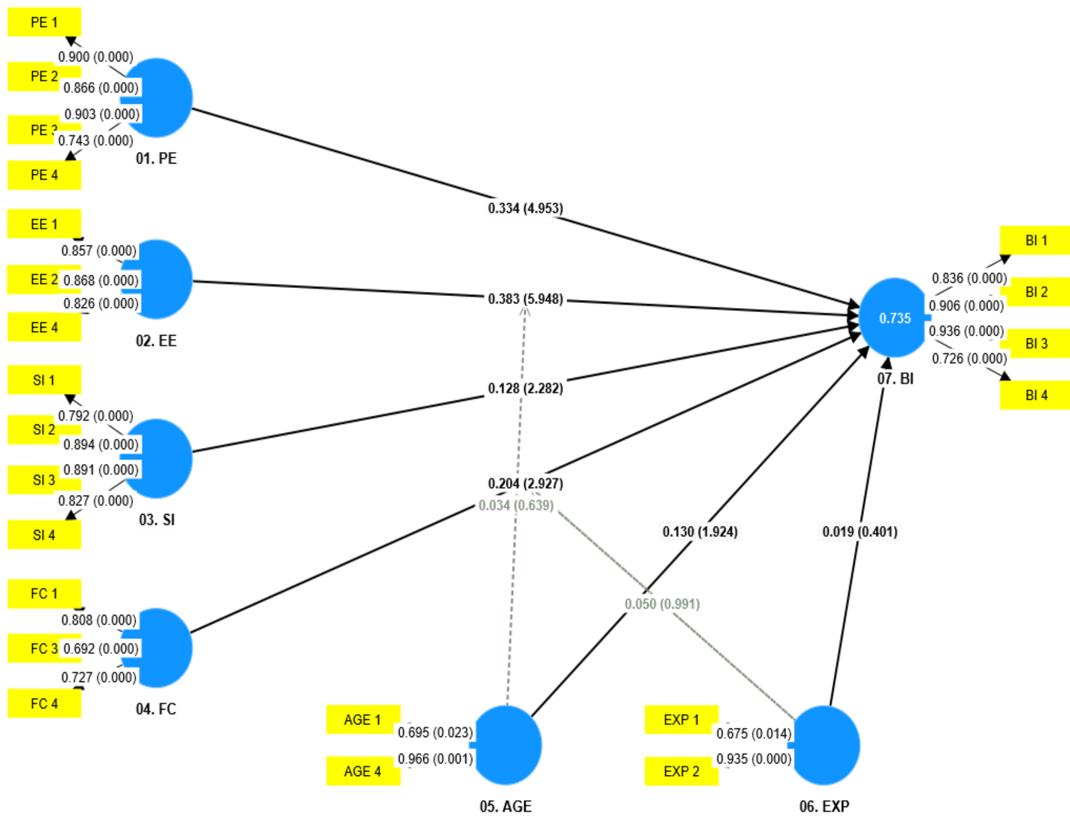

Figure 3.2 Structural model
[Source: Author's findings extracted via SmartPLS 4 by Ringle et al. (2022)]
Note. Path coefficients for the research model (excluding moderator main effect). Path value: beta coefficients (β), t-statistics value *p<0.05.
*Path coefficients and t-statistic values calculated via the SmartPLS4 bootstrapping method.

Subsequently, the **second part** of the **significance** and **relevance assessment** of the **path coefficient step** contains the evaluation of the moderating effect in relationships between constructs. Moderator models are likewise subject to measurement and structural model evaluation standards such as the path coefficient, t-statistics, p-value measurements, the f_sq effect size, and the slope plot graphical illustrations for the interpretation of moderation results (Hair et al., 2021). The R-sq is a necessary value to calculate the f-sq, the effect size that shows the degree to which the moderation contributes to the explanation of the endogenous construct and is calculated through f_sq= (R-sq_included-R-sq_excluded)/1-(R-sq_included) (Hair et al., 2021).

H5: Age (A) positively moderates the positive relationship between EE and BI such that young ages enhance the relationship between EE and BI. The study assessed the moderating role of Age on the relationship between EE and BI. Without the inclusion of the moderating effect (EE*A), the R-Sq of BI was 0.720. This shows that a 72% change in BI is accounted for by EE. With the inclusion of the interaction term, the R-Sq increased to 73,5%. This shows an increase of 2.08% in variance explained in the dependent variable (BI).

Further, the significance of the moderating effect was analyzed, and the results revealed a positive but **non-significant** moderating impact of A on the relationship between EE and BI (b=0.034, t=0.644, p=0.260), hence, **not** supporting H5 because the critical ratio (C.R.) (or t-values=path values/standard error (S.E.)), did not exceed 1.65 (0.644) and the significance level (p-value) was way more than 0.05 (0.260) (Abbad, 2021). As a result, moderator A does not moderate the relationship between EE and BI. In addition, the f-sq value is almost zero, 0.004, which is way too low than 0.02, the threshold small effect size value proposed by Cohen (1988), or even 0.005 proposed by Kenny (2018) (Hair et al., 2021), further supporting a very low relevance of moderating effect. Although there is no moderating effect for analyzing results, the graphical illustration with its slope plot in **Figure 3.3** illustrates that the lines are almost parallel and the steepness of the lines does not change with the change in the AGE from lowest to the highest value, proving the total lack of moderating effect.

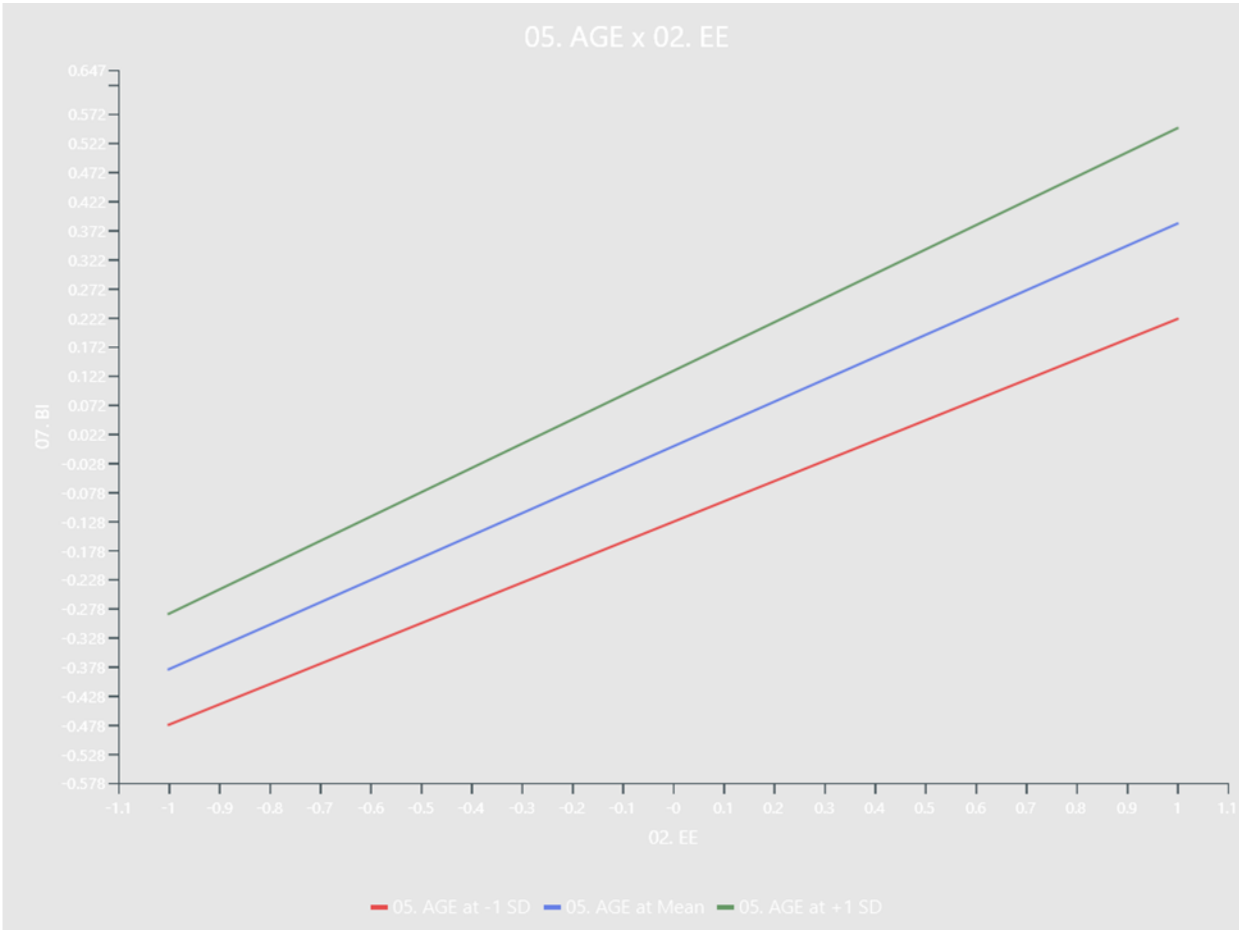

Figure 3.3 Slope plot of Age (A) moderator
[Source: Author's findings extracted via SmartPLS 4 by Ringle et al. (2022)]

Similarly, H6: Experience (E) positively moderates the positive relationship between FC and BI such that experience enhances the relationship between FC and BI. The study assessed the moderating role of Experience on the relationship between FC and BI. Without the inclusion of the moderating effect (FC*E), the R-Sq of BI was 0.732. This shows that a 73.2% change in BI is accounted for by FC. With the inclusion of the interaction term, the R-Sq increased to 73.5%. This shows an increase of 0.409% in variance explained in the dependent variable BI.

Further, the significance of the moderating effect was analyzed, and the results revealed a positive but **non-significant** moderating impact of Experience on the relationship between EE and BI (b=0.05, t=1.003, p=0.158), hence, **not** supporting H6 because the critical ratio (C.R.) (or t-value=path value/standard error (S.E.)), did not exceed 1.65 (1.003) and the significance level (p-value) was more than 0.05 (0.158) (Abbad, 2021). As a result, moderator E does not moderate the relationship between FC and BI. Additionally, the f-sq value is 0.011 less than the lowest band of the f-sq threshold value according to Cohen (1988), but it is placed between the medium and the large effect size scale according to Kenny (1988). Precisely speaking, the f-sq value is closer to the medium value of the scale since 0.01<**0.011**<0.025, meaning that it has just a slightly medium f-square effect size proving the low relevance of the moderating effect. In addition to the insignificant moderating impact in the relationship between EE and BI. **Figure 3.4** shows the different lines to be similar without steepness being presented in any of them. **Table 3.12** presents the results of the moderately affected relationships.

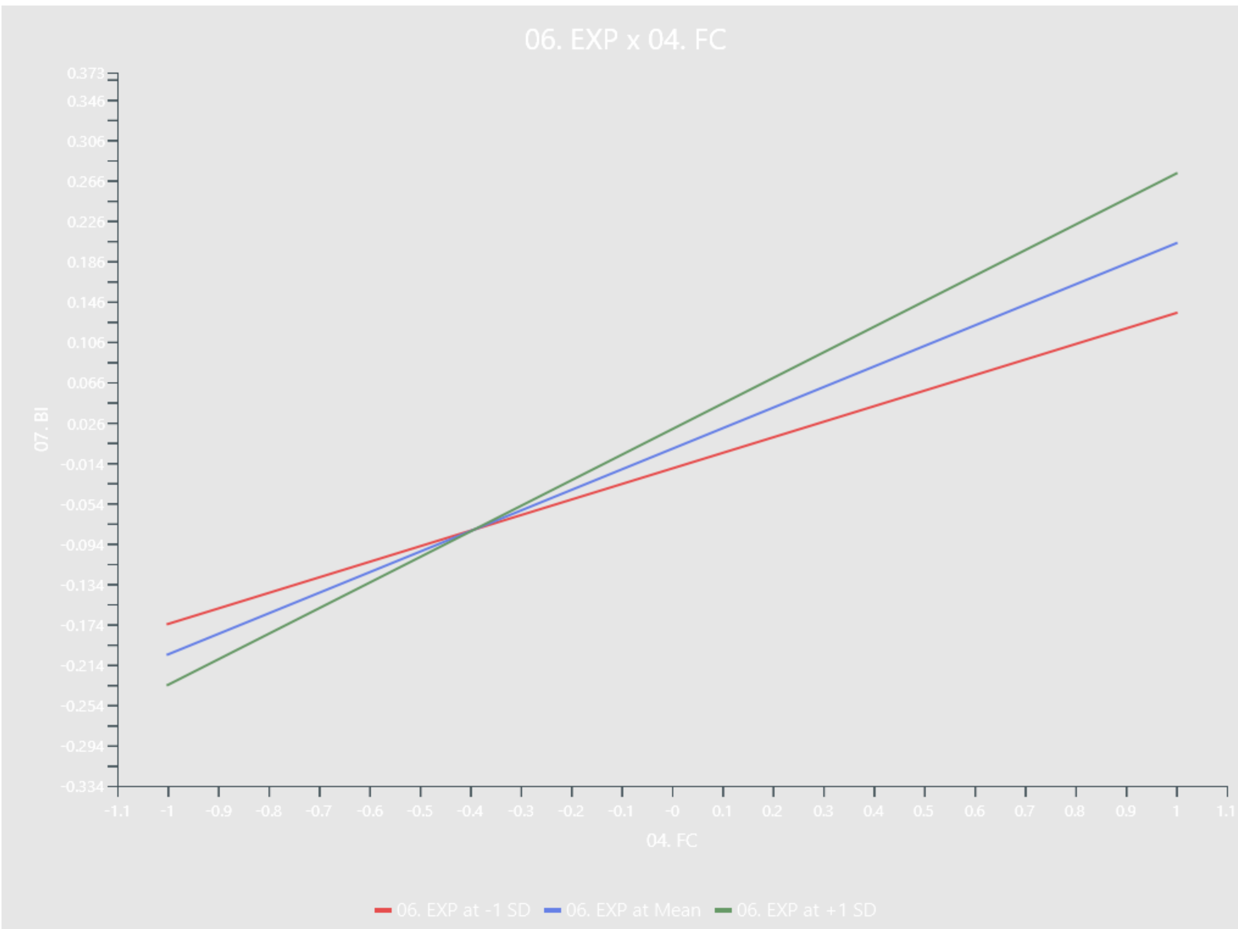

Figure 3.4 Slope plot of Experience (E) moderator
[Source: Author's findings extracted via SmartPLS 4 by Ringle et al. (2022)]

Table 3.12

Moderated Relationships [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Hypotheses	Beta Coefficient	Standard deviation	T-statistics	P-values	Decision
05. A x 02. EE -> 07. BI	0.034	0.054	0.639	0.261	Not Supported
06. E x 04. FC -> 07. BI	0.050	0.050	0.991	0.161	Not Supported

The next step of the structural model evaluation involves the **Explanatory Power assessment** (Naser & Jiroudi, 2016; Hair et al., 2021). The coefficient of determination (R_Sq), the measure of the model's explanatory power or in-sample predictive power is the variance explained in each of the endogenous constructs (Hair et al., 2021). Many researchers according to their conclusions graded differently the bands of R_Sq values. For example, Chin's (2018) R_Sq values of 0.67, 0.33, and 0.19 are classified as substantial, moderate, and weak respectively, without being taken for granted since the value of being considered satisfactory or not, is based on the field context. Instead, the range from -1 to +1 within which the values of R-Sq can vary is standard (Chin, 1998). The results showed that the R_Sq for the BI, the unique endogenous or dependent variable of this research model, is 0.735 which is a substantial value according to most social science disciplines (ResearchWithFawad, 2022).

Another metric that is part of the Explanatory Power assessment is the f_square metric which evaluates how an endogenous construct's R_Square value changes when a particular predictor construct is eliminated (Naser & Jiroudi, 2016). An indication of how much a relationship of interest is present in the population is provided by the effect-size indicator (Fern & Monroe, 1996). The f_square value which is also called f_square effect size is considered small, medium, or large if it is less than 0.02, 0.15, and 0.35 respectively (Cohen, 1988; Hair et al., 2019). The results of this study revealed that f_square effect size ranged from 0.001 (negligible) to 0.257 (high).

The Q_Square is the final measure to be considered for evaluating the Explanatory Power. Assessing the prediction accuracy of the path model, the Q_square was found to be 0.695 in this paper, showing a high predictive relevance as it was higher than 0.50 whereas if it was near 0 or between 0 and 0.25 it would demonstrate minor or medium predictive relevance correspondingly (Hair et al., 2019). **Table 3.13** shows the result of the R_Sq, f_Sq, and Q_Sq values of this model.

Table 3.13

Explanatory Power [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Predictor	Outcome	R_Square	f_Square	Q_Square
PE	BI	0.735	0.203	0.695
EE			0.257	
SI			0.048	
FC			0.106	
A X EE			0.004	
E X FC			0.011	

Predictive power assessment, also known as out-of-sample predictive power, is the final stage of evaluating a structural model (Hair et al., 2019). It determines how well a model can predict upcoming or new observations by estimating the prediction error in the indicators of a specific endogenous construct using the PLS_predict statistic procedure (Hair et al., 2021). The indicators' metrics are compared with a linear regression model (LM) benchmark after a linear regression of each of the endogenous (dependent) construct's indicators is run on the indicators of the exogenous (independent) constructs in the model (Hair et al., 2021). These metrics are the root mean square error (RMSE) and the mean absolute error (MAE), with the former being more widely used unless there are instances in which prediction errors have a very nonsymmetrical distribution (Hair et al., 2021). If the prediction errors of RMSE (or MAE) are higher compared to the naïve LM benchmark for all indicators, the model lacks predictive power Hair et al., 2019). In case the same analysis with the same results in terms of errors takes place but appears to be addressed to most indicators, the model has low predictive power (Hair et al., 2019). Should the same scenario with the same results now be addressed to the minority of indicators, the model indicates a medium predictive power whereas if none of the indicators have higher RMSE values to the LM benchmark, the model has high predictive power (Hair et al., 2021). In our study, after observing the PLS-SEM and LM MV prediction error histograms, it was not observed any serious asymmetrical distribution that led us to use the PLS-SEM_RMSE instead of PLS-SEM_MAE to compare its values to its corresponding values of LM-RMSE. **Table 3.14** illustrates that none of the indicators' RMSE values were higher than LM-RMSE indicating a high predictive model power.

Table 3.14

Predictive Power [Source: Author's findings calculated via SmartPLS 4 by Ringle et al. (2022)]

Indicators	Q^2predict	**PLS-SEM_RMSE**	PLS-SEM_MAE	**LM_RMSE**	LM_MAE
BI 1	0.430	0.789	0.633	0.876	0.708
BI 2	0.588	0.712	0.549	0.781	0.598
BI 3	0.661	0.711	0.542	0.795	0.607
BI 4	0.325	0.954	0.735	1.075	0.833

Note. The columns in Bold (3&5) are only compared for the extraction of the model's predictive power.

5 Chapter- Discussion and Implications

The theoretical model presented is unique, from the perspective that it uses a UTAUT model by Venkatesh et al. (2003). The modification lies in using fewer moderators than those presented in its original form, namely the age and the experience excluding the gender and the voluntariness of use. In addition, it excludes the dependent (endogenous) variable of UB for the same reason as Puspitasari et al. (2019) do. This study was designed to investigate and identify the factors in the UTAUT that affect onboard drone adoption for maritime operations. The model presented examines whether PE, EE, SI, FC, A, and E moderate and predict BI. More specifically, it was proposed that the four determining components mentioned above, PE, EE, SI, and FC positively affect the interest in onboard drone use in maritime operations. Furthermore, it is hypothesized that both the A and E moderators positively moderate the relationships of EE and FC with BI respectively. Data from 110 samples in Greece and the Netherlands, consisting of seafarers and students from merchant academies with over a year of sea experience, were used to test the offered hypotheses. The survey used for the empirical study was performed from the period of September to November 2023. The sample size was calculated via the G*Power statistic program 3.1.9.7 mainly depending on the type of model and the number of predictors (Memon et al., 2020). The following are the theoretical and practical ramifications of the study's findings.

First, the research model explains 73,5% of the variation in the behavioral intention of onboard drones.

Second, in terms of connections between the model's components and BI, all the hypothesized relationships between the dependent or endogenous variable BI and the independent or exogenous variables PE, EE, SI, and FC were statistically positively significant.

More analytically, the results revealed that EE was the construct that most significantly increased behavioral intention toward onboard drone adoption in maritime operations ($\beta = 0.383$, $p<0.05$).

That is when people assume that utilizing technology will be effortless (Davis, 1989; Venkatesh & Davis, 2000). This finding is consistent with previous findings in technology acceptance research (Marchewka et al., 2014; Martins et al., 2014; Aydın & Burnaz, 2016; De Sena Abrahão et al., 2016; Puspitasari et al., 2019; Chao, 2019; Abbad, 2021;), whereas it is opposite to others (Jackson et al., 2013; Baptista & Oliveira, 2015; Hwang et al., 2019; Rahmaningtyas et al., 2020).

According to the results, the second most important factor in this study is the belief that technology can improve an individual's performance at work. This belief is represented as PE in the UTAUT model, and it is consistent with previous research that found this variable to be one of the primary factors influencing the intention to adopt and use technology such as Jackson et al. (2013), Martins et al. (2014), Baptista and Oliveira (2015), Aydın & Burnaz (2016), De Sena Abrahão et al. (2016), Puspitasari et al. (2019), Chao (2019), Rahmaningtyas et al. (2020), Abbad (2021), Khanh et al. (2023). However, it contrasts with Marchewka et al. (2014) who did not demonstrate this variable as a relevant factor. As of right now, these study's findings are consistent with Davis' (1989) TAM model, which holds that information technology's PE and EE are always the main factors influencing its adoption in businesses and laying the groundwork for attitudes toward using a particular system, which in turn establishes the intention to use and, ultimately, the actual usage behavior.

Subsequently, while still having a favorable impact on BI, the remaining constructs, SI and FC, do so but less strongly than the study's earlier independent variables. FC referred to as “the resources and assistance that consumers perceive to be available to carry out a behavior” (Venkatesh et al., 2012) is the next most significant predictor of this study, in contrast to Marchewka et al. (2014) and Baptista & Oliveira (2015), but in line with previous research on this component (Puspitasari et al., 2019; Marsofiyati et al., 2021).

Finally, this study validates the beneficial effects of SI, or the expected influence of other people on the decision of the user to start and continue using technology (Momani, 2020). As per the conclusions drawn by Marchewka et al. (2014) and De Sena Abrahão et al. (2016), this effect is significant, but it appears to be the least powerful determining factor among all the factors included in the theoretical model of this paper. This contrasts with the results of Jackson et al. (2013), Puspitasari et al. (2019), Rahmaningtyas et al. (2020), and Marsofiyati et al. (2021) who while finding the SI factor to be significant, also demonstrated that it was one of the most salient variables for BI, in contrast to our findings. Furthermore, Baptista and Oliveira (2015), Aydın & Burnaz (2016), Yoo et al. (2018), and Abbad (2021) found the SI factor to be non-significant, totally contradicting the results of this work.

Overall, the sequence in the level of significance of each construct, namely EE, PE, FC, and SI, is also confirmed by one of the findings of explanatory power assessment and specifically, the f_square metric, the values each one of the above variables of which were 0.257, 0.203, 0.106, 0.048 respectively, confirming the level their significance is valid.

In this study, A and E were tested as moderators. However, the hypotheses that these moderators moderate are rejected meaning that the research model did not validate the influence of age and experience on effort expectancy over behavioral intention and facilitating conditions over behavioral intention respectively. Hence, age and experience do not play any significant role in the relationships between the constructs of the model and its dependent variable which was initially hypothesized to be moderated.

Interestingly, it was demonstrated that no findings from the technology system adoption study had even attempted to explore the important impact that experience moderators had in their research. The only study to look at including moderator experience was Puspitasari et al. (2019); however, it was ultimately rejected because it did not support the research being in line with the conclusions of this study.

On the other hand, gender and age were two of the moderators of Venkatesh et al.'s (2003) original UTAUT that were frequently noted to be included in studies on the adoption of information technology. Specifically, while Hwang et al. (2019) confirmed that age played a substantial moderating influence on the adoption of new technology, the findings of Marchewka et al. (2014), Martins et al. (2014), and Puspitasari et al. (2019) were in line with this study.

5.1 Theoretical Implications

This study represents the first attempt to examine empirically the relationship between behavioral intentions and the UTAUT core components (PE, EE, SI, and FC), in the context of onboard drone use in maritime operations. The study's findings have ramifications for both researchers and managers of maritime operations in this area. Researchers will find that this study adds a great deal of theoretical value to the body of literature by laying the groundwork for future research and further refining specific models of acceptance. Furthermore, this paper makes an academic contribution because it combines some of the most used constructs in literature to predict Onboard Drone Adoption in Maritime Operations into a single model of intention to adopt. The perspectives of cadets, the seafarers of the future, who already have some experience but are not yet active, experienced seafarers and sea operation managers are represented in this paper.

5.2 Managerial Implications

The results of this thesis highlight important managerial ramifications for the use of drones onboard ships during maritime operations. The ease of use of drones or effort expectancy is, first and foremost, the most significant predictor of this study. Drones can be used more effectively and widely accepted if the operation procedure is made simpler and user interfaces are made easily accessible. Managers should give priority to training programs that improve users' understanding and skills in drone operations, as the study's alignment with the PE construct of the UTAUT model and the fact that drones can significantly improve surveillance, inspection, and data-gathering tasks lead to better-informed decision-making and operational efficiency. This will ensure that perceived performance improvements match actual outcomes. Organizational infrastructure must support drone technology in terms of facilitating conditions. This includes not only the technological elements, including data processing and maintenance facilities but also the policies and processes that control drone use and guarantee safety as well as regulatory compliance. Lastly, in terms of social influence, managers ought to take a proactive approach to educate staff members about the advantages and possibilities of drone technology while also clearing up any misunderstandings or concerns they may have.

6 Chapter - Limitations and Future Research

Notwithstanding the significant theoretical and practical ramifications of this work, the following limitations still exist and may open the door to more research on onboard drone applications in maritime operations. First, the sample size of this study was 110, just one response more than the cut-off requirement of 109 according to Memon et al. (2020). To produce a more thorough research, future studies should optimize samples including a wider range of respondents (i.e. seafarers, operation managers) enabling a more significant generalization of the findings. At that point, it is of great importance to report that one of the reasons for not easily reaching a substantial number of submitted surveys was that during the interaction with seafarers trying to persuade them to take part in the survey, a vast number of them not only refused to fill it in but also expressed their discontent with the concept about onboard drone implementation with most of them answering generally and vaguely like "drones cannot be applied to X type of ship", or even worse " drones cannot be applied to any type of merchant ships", or "none of the officers of the ship fancy filling this survey in" without reasoning it out.

Second, following the previous argument where it was stated that although there was a kind of interview/interaction with many seafarers, the main methodological approach used to obtain the data for this study was the quantitative method. Using a single type of methodology for data collection may have limitations. Specifically, the research tool for this study was a self-reported questionnaire. Respondents may not always give their genuine opinions while answering questions on a questionnaire, which could cause inaccuracies in the findings. Hence, a mixed methodological approach that incorporates both qualitative and quantitative methodologies may aid researchers in developing more accurate models and assessing those models across cultural boundaries, as demonstrated by Puspitasari et al. (2019), who employed both qualitative and quantitative research methods—interviews and questionnaire distribution to identify the factors that influence users' use of an integrated information system.

Third, the survey was carried out using a (cross-sectional) design at a specific point in time. As new knowledge and experiences are gained, seafarers' and operation managers' opinions of PE, EE, SI, FC, and BI about the adoption of onboard drones may shift. Thus, a longitudinal design might be used in subsequent research to get more precise data from a particular population.

Fourth, a restricted category of marine businesses and their activities were the focus of this study, which was carried out in Greece and the Netherlands. Future research should therefore concentrate on the maritime industry's diversity, which includes a range of vessel types, operations, and geographical regions that represent the industry as a whole.

Fifth, our study evaluated the intention to use the innovation rather than its actual application. The UB construct which is one of the dependent variables in the original UTAUT model by Venkatesh et al. (2003) relies more on socio-behavioral research (Jackson et al., 2013). Earlier studies in the technology adoption context conducted have included the UB construct as a predictor such as Martins et al. (2014), Baptista and Oliveira (2015), Yoo et al. (2018), Rahmaningtyas et al. (2020), Abbad, (2021), Marsofiyati et al. (2021).

Finally, while using experience and age as moderator variables makes sense, it also limits our understanding of potential moderators. Thus, future research may take into account modifying the study model to include new moderators like technological affinity, risk perception, and trust.

7 Chapter- Conclusion

The most typically analyzed themes in IT/IS literature are IT adoption models, used more often to investigate factors influencing a particular technology's intention to use or the use itself in a variety of human and organizational contexts (Martins et al., 2014).

The main goal of the current study was to investigate the factors that influence seafarers' decisions to utilize drones while on board during maritime operations.

To do so, the empirical study developed a conceptual model which was a modified form of the Venkatesh et al. (2003) original UTAUT model involving the five main constructs (PE, EE, SI, FC, BI) and two moderator variables A and E. The results revealed that the model had high internal consistency reliability and construct validity whereas its explanatory and predictive power were both substantials. The findings imply that behavior intentions were most significantly influenced by EE, the key factor of this research, and PE, the second most powerful predictor of this study accounting for the most robust predictors of onboard drone adoption in maritime operations. The other two remaining main determining components stated in a declining significant order, FC and SI both also had a positive effect on behavioral intention but less significant impact compared to the two previous main constructs.

As for the moderators, neither A nor E was significant to support their moderated relationships between effort expectancy and behavioral intentions and that between facilitating conditions and behavioral intentions respectively. The explanation for the moderators' findings relies on the theory of acceptance and use of technology. According to this theory, the impact of the effort expectancy construct on behavioral intentions is "significantly moderated by older women and older workers in early stages of experience" whereas the the impact of facilitating conditions construct on behavioral intentions is "highly moderated by older workers with increased experience" (Momani, 2020). Because female respondents make up 2.7% of the sample, older respondents make up 15.4%, and respondents with "increased" experience make up 9%, none of the conditions are met in this study, confirming the insignificance that the theory has already implied. As a result, the insignificant moderating effects extracted in this research seem to make sense.

Finally, answering the third sub-research question, it is concluded that not only can maritime industries' management foster the acceptance and integration of onboard drones but also leverage their full potential to enhance operational efficiency and safety in the maritime sector. This can be accomplished by clearly communicating and demonstrating the benefits of onboard drone technology in improving operational efficiency and effectiveness (PE), investing in user-friendly drone systems and providing staff with thorough training (EE), ensuring that the necessary infrastructure and support are in place as well as the procedural and policy frameworks that govern their use (FC) and fostering a positive organizational culture towards drone adoption (SI).

Overall, the present study integrates a novel and cutting-edge approach to drone operations on board with an analysis of Venkatesh et al.'s (2003) model theory, offering a useful framework for future research and practical implications for maritime sector decision-makers.

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Appendix I. Technology State of Play/Overview of UAV Technology in Shipping

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
A. Environmental pollution monitoring				
1. Marine debris **monitoring/pollution** characteristics assessment	Machine/Deep learning technology-based segmentation model.	**UAV** Aerial survey image by drone with a 20 MP camera. **Method** Mapping method.	Ongoing process.	Song et al. (2022)
2. **Environmental** pollution source/location **tracking**	1. Target tracking technology-visual tracking of the ground (attitude estimation and image processing algorithms): a. location technology, b. drone tracking technology. 2. UAV sensing technology (design algorithms). 3. Reynolds equation/Turbulence model.	**UAV** Multi-UAV vision/target motion model. **Method** Not a specific one.	In the experimental stage.	Shen et al. (2023)
3. Offshore ships' **emission detection (COx, SOx, NOx, PM)** with simultaneous movements **and drone routing problem** (used to schedule a drone to detect the emission status of the ships while the ships are moving in the ECA)	1. High-efficiency monitoring method. 2. Drone-sniffing technology (highly microsensor system). 3. Remote sensing measurement technology like LiDAR, and Differential Optical Absorption Spectroscopy. 4. Nonlinear program. 5. Heuristics algorithms (Genetic/Dichotomy/Sequence-based construction algorithms). 6. Lagrangian relaxation-based method. 7. Mixed Integer linear programming model (MILP model).	**UAV/Method** 1.Rotor drone equipped with sulfur-sniffing device-flight controller-fast screening system-4G network data transmitter-real-time data monitoring (additionally, able to have photoelectric equipment-airborne AIS-airborne VHF-hyperspectral imaging equipment-sea search radar-oil pollution	Ongoing development of drone application.	1. Hu et al. (2023) 2. Xia et al. (2019) 3. Anand et al. (2020) 4. Deng et al. (2022) 5. Zhou et al. (2022) 6. L. Shen et al. (2022)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
		sampling equipment). 2. SDMU Model with the aid of ABC and the improved ABC Algorithm. 3. Drone routing problem solution by heuristics and Lagrangian method.		
B. Anti-piracy monitoring method				
UAV pheromone-based swarm **anti-piracy** monitoring method.	1. Conventional sweep monitoring. 2. Swarm monitoring.	**Method** Pheromone method for UAV swarm monitoring.	In the experimental stage.	Zhang et al. (2018)
C. Inspections/Surveys				
1. Aerial (UAV) Free-drifting iceberg **survey.**	Aircraft-deployable GPS tracking tags.	**UAV** A fleet of UAVs along with remotely operated vehicles (ROVs) were used. UAV models were controlled with a 7-channel, spread-spectrum, digital-proportional radio control system. **Method** UAV launches were executed to land on the iceberg and drop the GPS tag safely.	Although in operation, ameliorations need to be set to accurately capture the icebergs' motions.	McGill et al. (2011)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
2. Large surface **inspection** such as ship hulls and water tanks by a fleet of UAVs.	A coverage algorithm is separated into Traveling Salesman Problems (Part-TSP) and a cooperative frontier approach (Coop-Frontier).	**UAV** A fleet of UAVs.	It is a simulation model, but it is expected real UAVs to be used in future evaluations.	Grippa et al. (2022)
3. Offline trajectory planning for fully automated visual **inspection** of predefined areas on a component, known also as Point of Interest (POI) (e.g., ship hulls).	1. Rapidly Exploring Random Tree Algorithm (RRT)/ Redundant Roadmap Algorithm. 2. Local Coverage Algorithm (LCA). 3. Ant Colony. Optimization (ACO) 4. Particle-Swarm-Optimization (PSO). 5. Artificial-Bee-Colony (ABC). 6. Firefly Algorithm (FA). 7. Genetic Algorithm (GA).	**UAV** UAV (not of specific requirement). **Method** Offline path planning/ Trajectory.	In its infancy- Only tested in a simulation environment.	Wanniger et al. (2020)
4. Port and content of cargo **inspections** (transport safety/port and quays technical infrastructure assessment).	1. Developed algorithms: a. Anaglyphic method, b. Shutter glasses method. 2. Epipolar images. 3. Matrix concept. 4. SVD (Singular value decomposition).	**UAV** An Olympus PEN E-P2 camera from Microdrones md4-1000 UAV. **Method** Epipolar images are generated using the fundamental matrix by images taken with non-metric cameras. Stereoscopic images were then produced using	In operation.	Paszotta et al. (2017)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
5. Automatic ship **detection** by UAV.	1. A multi-level ship detection algorithm. 2. Rotation Invariant descriptor: a. Histogram of oriented gradients (HOG), b. Fourier basis. 3. Optical remote sensing data (ORS) data.	anaglyph and shutter system methods. **Method** A two-phase ship detection algorithm to solve the problem of scale and rotation change in complex background, the result of which is compared with the threshold segmentation algorithm.	A model with non-satisfactory results since the ship and its wake are identified as a whole unit.	Dong et al. (2019)
D. UAV landing process				
1. UAV autonomous recovery **landing** on underway ships in a broader way of conditions even in harsh seas and environmental conditions.	Active learning predictors/acoustic sensors with an extended Kalman filter (EKF)/field guidance algorithms.	**UAV** Quadrotor UAV of PX4 software using geometric hierarchical dynamic visual servoing.	In the lab context.	(Ross et al., 2021)
2. UAV autonomous **takeoff** and **landing.**	Feed-forward image-based visual servoing (FF-IBVS)/ vision sensors/pan-tilt camera.	**UAV** Quadcopter with & without a gimbal camera.	In simulations and real-world flight experiments.	Cho et al. (2022)
E. Communication Facilitator				
1. UAVs as **Hybrid** satellite-terrestrial maritime **communication** Network.	A hybrid maritime network is set up including mobile users (ships), UAVs, TBSs (terrestrial base stations offering high-rate communication services along coastal waters), and satellites. UAV kinematics, tolerable interference, backhaul, and UAV communication energy are the constraints, whereas	**Method** Spectrum is shared and efficient backhaul between UAVs and satellites is developed.	Under the progress of improving the quality of service.	Li et al. (2020)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
	large-scale CSI and AIS are the availabilities.			
2. Ships' **antennas** smarter **testing.**	1. GPS sensors. 2. Redundant communication links. 3. Additional rotors beyond the lift. 4. Software logic.	**UAV** Drone with multiple GPS sensors. **Method** A drone operating as a satellite simulator to check stabilized directional antennas. The antenna will constantly face the moving drone since it receives a signal indicating that it is indeed a satellite.	In operation.	Marianne Harbo Frederiksen & Mette Præst Knudsen (2018)
F. SAR OPERATIONS				
1. Offshore marine **SAR** Operations.	1. Specially designed algorithms for helicopter maneuver tracking. 2. Artificial Neuronal Networks. 3. ICARUS (Integrated Components for Assisted Rescue and Unmanned Search). 4. Victim detection algorithms.	**UAV** Fixed-wing UAVs with on-board cameras. **Method** 1. Provider of topographic mapping and assistance to SAR operators. 2. Moving target tracking 3. Emergency delivery of lightweight	In operation.	Yeong et al. (2015)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
		goods and first-aid kits. 4.Communication relay server.		
2. Nearshore Marine **SAR** Operations.	1. Aerial rescue robot Pars by the Iranian lab. 2. Riptide project. 3. UAV equipped with a Kinect and a Surface Pro device.	**UAV** Multi-rotor UAV. **Method** 1. Able to save up to three lives at a time of distressed swimmers near the shore. 2. Life ring equipment delivery. 3. Additional night vision capabilities.	In operation.	Yeong et al. (2015)
3. Fully autonomous **SAR** Operations.	1. UAV technologies 2. Real-time computer vision 3. Deep learning techniques. 4. GNSS techniques. 5. Computer vision algorithms.	**UAV** Fully autonomous rescue hexacopter UAV with a YOLOv3 architecture on the embedded autonomous computing machine device. **Method** Open water winter swimmer in peril detection by a fully autonomous rescue UAV doing time-	In the process of being used in many more SAR terrains or environments rather than the open water swimming rescue environment.	Lygouras et al. (2019)

Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
		crucial life-saving tasks in a fully unsupervised manner.		
G. Delivering packages				
1. Shore-to-ship-UAV **delivery** at anchorage in harbors and vice versa.	Successful delivery of goods/documents/spare parts/emergency supplies of medicines that benefit from cost reduction, environmental impact reduction such as small carbon footprint, air pollution absence, delivery time decrease, and possible replacement of launch boat deliveries.	No specific method or type of drone is proposed.	In operation.	1.Krystosik Gromadzińska (2021) 2.Marianne Harbo Frederiksen & Mette Præst Knudsen (2018)
H. Intelligent procedures				
UAV intelligent **spray-painting systems** (UAV-ISP).	1. Multiobjective particle swarm algorithm and ant colony algorithm. 2. Stability control method for the UAV based on the linear active disturbance rejection control. (LADRC) algorithm 3. Mission Planner ground station software to solve the stability control problem of UAVs. 4. Newton-Euler equation. 5. Catenary theory. 6. Mathematical model of the UAV	**UAV** A six-rotor UAV, ground follower vehicle, and spray mechanism with adaptive nozzle **METHOD** A 3D model of the ship was obtained in a 3D modeling environment. Paint-path optimization is done using the swarm algorithm. Ant	On an experimental level simulation for an accurate painting path for part of the hull body (outer panels of the ship). Further research is to be done for broadening the spray-painting method and for ameliorating the stability	Cai et al. (2021c)

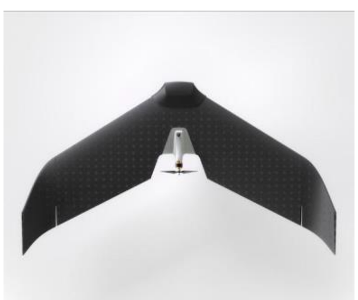
Type of Operations	Type of Technology	UAV/Method	Implementation Stage	Reference
	spray-painting system with multi-load coupling.	colony algorithm is used for the final spray-painting path, followed by a force analysis and the design of the stability control system.	of the UAV and the efficiency along with the quality of the outer panel ship painting method.	

Appendix II. Drone Type

1) **Multirotor**

Source: Krystosik-Gromadzinska, 2021

2) **Fixed-wing**



Source: Forsman & Westergren, 2019

3) **Single rotor**

Source: Forsman & Westergren, 2019

4) Fixed-wing Hybrid

Source: Forsman & Westergren, 2019