

Christian Schan

# Use of smart glasses in order picking operations

Assessment of a pick-by-vision solution with the Hololens

Master's thesis in Global Manufacturing Management  
Supervisor: Fabio Sgarbossa

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# Abstract

Order picking operations have attracted a lot of attention from researchers in the last decades as these are identified as the most time-consuming, labour-intensive and expensive activities for most warehouses. To remain competitive, warehouse managers always keep searching for new alternatives of picking systems with the goal of increasing picking productivity without raising significantly their expenses. However, investing in a new picking system requires gaining insight from the different options beforehand, which is difficult without testing the latter. Decision-makers are therefore skeptical about whether the gain in productivity is worth the related investments.

In this recent era of Industry 4.0, numerous innovative technologies have emerged, with augmented reality (AR) being one of the most promising ones as it can be applicable in many fields. Paired with AR, smart glasses present a great potential to assist operators in warehouse picking activities as they do not require the use of hands while having the abilities to display relevant information to the picking locations at eye-level.

The present paper is then focused on the use of smart glasses in order picking operations. The main objective of the study is to perform an assessment of a pick-by-vision system from both productivity and economic perspectives and to compare it with other picking systems. The inclusion of the economic perspective in the evaluation of the pick-by-vision system is the main contribution of this research.

The methodology has been the following. First, the literature has been the main source of input to know the state-of-the-art of pick-by-vision systems. A pick-by-vision system using the Hololens was then developed for this specific study in order to conduct the evaluation. To measure its picking performance in terms of picking time and picking errors, several test people were solicited to accomplish order picking tasks using the developed Hololens solution in the pilot warehouse set up in the Logistics 4.0 laboratory. Following the experiment, results from the measurements were integrated in an economic model which calculates an hourly cost function of a given picking system. A comparative analysis was then conducted with five other picking systems which are barcode handheld, RFID tags handheld, pick-by-voice, pick-by-light and RFID pick-by-light systems, built on the work of some other researchers.

From the calculations of the hourly cost functions of each picking system, it has been possible to determine the most convenient picking system depending on the demand from the customer orders (translated in the number of requested picking rows). The considered pick-by-vision revealed to be the most profitable system for most of the cases where the number of requested row  $n_R$  was lower than 170 rows/hour, but was outperformed by the RFID pick-by-light for higher  $n_R$ s. A qualitative assessment of the pick-by-vision system was also added in the discussion. These findings can be beneficial to warehouse managers who are in the process of deciding for investments in a new picking system.

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# Acknowledgement

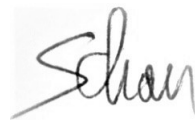
The present thesis is the final work of my Master of Science program in Global Manufacturing Management at the Department of Mechanical and Industrial Engineering, at The Norwegian University of Science and Technology (NTNU). A major part of the research has been conducted in the newly established Logistics 4.0 laboratory.

First of all, I would like to show my immense gratitude for Fabio Sgarbossa, my supervisor who has given me valuable advice, shared his insight from his experience working with warehouses and guided me throughout the semester for this master thesis. Then, I am very grateful to Giuseppe Frapagane for having co-supervised me, provided some clearance for the questions I raised as well as some useful comments on my work. Feedback during the two thesis presentations from Jan Ola Strandhagen, Erlend Alfnes, Olumide Oluyisola and Sven-Vegard Buer was also greatly appreciated.

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Finally, my special thanks are extended to the authors of Hanson et al. (2017), who accepted to share the application they had developed, so that I could get inspiration to build up my work from an existing solution.

Christian Schan

A handwritten signature in black ink, appearing to read 'Schan', is positioned below the printed name. The signature is written in a cursive, flowing style.

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# Introduction

For the past decades, companies have considered order picking as the most labour-intensive, time-consuming and costly activity in warehouses (Battini et al., 2015; De Koster et al., 2007); the related costs have been estimated to be as much as 55% of the total warehouse operating expenses, while warehousing accounts approximately 20% of companies' logistics costs (De Koster et al., 2007). Poor performance in order picking can result in inability to fulfill a satisfactory service level and can cause high operational costs for the warehouse and for the rest of the supply chain. As a consequence, improving order picking performance has become one of the top priorities for warehouse managers (Battini et al., 2015).

As of today, the majority of warehouses uses manual workforce to perform order picking (about 80% of western Europe companies according to De Koster et al. (2007)). Traditionally, operators are given a paper checklist on which information such as customer orders and products' location are written to perform order picking. This classical pick-by-paper system is very time-consuming and prone to errors and it is commonly used in many warehouses (Hanson et al., 2017; Battini et al., 2015). Therefore, different innovative picking systems whose primary objective is to enhance the productivity of the picker with regard to reducing the time needed to fulfill a picking order, as well as potential picking errors, have been designed over the years, in line with the recently developed technologies (Battini et al., 2015).

## 1.1 Problem statement and scope

To remain competitive, companies try to embrace the industry 4.0 movement and opt for digitalization of their operations to improve their overall performance, but they struggle to determine whether an investment in a new technology is worthy, depending on the benefits and the disadvantages the technology presents. Thus, increasing the picker's productivity

should not be the only objective that is worth investigating (Grosse et al., 2015). Another very important aspect to consider, which has been given little attention to in the literature (Battini et al., 2015), is finding the middle ground between the costs of investment in a given picking system and the actual return on investment related to the invested picking system. In other words, economic evaluation should be conducted at the same time as performance evaluation of a given order picking system.

In this regard, Battini et al. (2015) conducted a comparative study between different paperless picking systems and introduced an economic model to evaluate them. The studied picking systems are barcode handheld, RFID (Radio frequency identification) tags handheld, pick-by-voice, traditional pick-by-light and RFID pick-by-light. Each of the mentioned technologies have their own benefits and disadvantages; for instance, the barcode handheld scanner requires the use of one hand and voice-picking requires the picker to confirm the picking vocally, which can be tedious and somehow time-consuming.

A suggested direction for further research is to enrich this economic comparison by including other order picking systems. Hence, this present paper aims to extend the work of Battini et al. (2015) and focuses on exploring the newly engineered picking system that has emerged with the industry 4.0 era: the pick-by-vision system.

Augmented reality (AR) is one of the most innovative technologies that has attracted attention in recent years and is applicable in many fields (Syberfeldt et al., 2017). AR can be paired with various devices such as smartphones, tablets or smart glasses. The pick-by-vision system involves the use of smart glasses, which can also be described as head-mounted displays. Being a hand-free device capable of providing visual and sometimes audible information to its user is one of its main advantages, which is particularly relevant in order picking operations where the operator has to travel within a warehouse, searching for the to-be-picked items and most often uses both of his/her hands to physically pick the products. The model used in this research is one of the most popular smart glasses models in the market, the HoloLens by Microsoft.

The research questions addressed in this report will be the following:

- 1. What features should a pick-by-vision system include to best support an operator in order picking operations?**
- 2. What are the gains in terms of productivity by adopting a pick-by-vision system?**
- 3. In comparison to other picking systems, how profitable is the investment in a pick-by-vision system? What are the potential advantages and drawbacks?**

Answering the first research question will not necessarily contribute to the scientific knowledge in this research area, since some functional pick-by-vision systems have already been developed in the past, but it is an essential step to take to achieve the objective of the present study.

The main objective of this thesis is then to assess the pick-by-vision system, from both productivity and economic perspective and to compare it with other order picking systems,

in line with the findings of Battini et al. (2015). The results will be beneficial inputs to support warehouse managers when deciding to invest in a new order picking system. A sub-objective in this thesis was to develop an efficient in-house pick-by-vision system that will be tested in the laboratory.

The present research is centered on order picking operations, other warehousing activities are disregarded. Furthermore, as the focus is on manual order picking operations, automated picking systems will only be briefly mentioned here.

As a pick-by-vision system can be designed in various ways with different models of smart glasses and include different potential visualizations to assist the work of an order picker, the present paper does not cover the assessment of the pick-by-vision systems in a global way. Instead, the evaluation is done only on the pick-by-vision system which is developed for this particular study.

## 1.2 Methodology and outline

The methodology of the present student adopts mostly quantitative methods, meaning that it includes the measurement and the analysis of some parameters that are quantifiable (Kothari, 2004). However, the assessment of the pick-by-vision system does not only include quantifiable variables, it also discusses the pros and cons of such a system as well as comparing it with other picking systems in a descriptive way, hence part of the study will be qualitative as well.

The first step of the present research is to gain in knowledge in order picking from the literature, which will be presented in the theoretical background chapter. Then, a literature study is conducted to know the state-of-the-art of what has already been researched in the application of smart glasses in order picking. This will confirm the motivation of this master thesis and clarify its contribution. Results from this literature study will bring answers to research question 1 and will be used as a basis to build and implement our own pick-by-vision solution. An explanatory video about the developed pick-by-vision system can be accessed with the link: [https://www.youtube.com/watch?v=rBW\\_Y8xUeE0](https://www.youtube.com/watch?v=rBW_Y8xUeE0)

A pilot warehouse has been designed and set up in the logistics 4.0 laboratory where some experiments with the Hololens application will take place. During the tests in the laboratory, picking times and errors will be measured from several test persons using the pick-by-vision application, which answers to research question 2. Following the results from the experiment, the economic model introduced by Battini et al. (2015) is used to conduct the assessment of the pick-by-vision system to answer to research question 3. The latter will then be compared to other order picking systems accordingly to the findings of Battini et al. (2015) and some sensitivity analysis will be performed to check the robustness of the results.

### 1.2.1 The literature study

First a set of keywords has been defined. The list of the selected keywords included smart glasses, head-mounted display, economic evaluation, assessment, performance, augmented reality, warehouse picking, order picking, pick-by-vision. These keywords have then been combined with the "AND"/"OR" operators to generate relevant searches. Google scholar has been used as the main literature database, and some articles have been selected from the searches from Oria.

From the different searches, a superficial selection of the articles is first done by reading the titles, then reading the abstracts enabled a further selection. From the references cited in selected articles, some relevant articles have also been retrieved. Some papers have also been used following some recommendations from the supervisor and co-supervisor of the present thesis. Finally, the use of the web program Mendeley has proven to be effective. Based on the selected papers that have been stored in the personal library, Mendeley has been able to suggest other relevant articles.

It is also important to get a little insight of what has been achieved in the industry, e.g. logistics solutions providers who are selling pick-by-vision systems to other private companies. For this purpose, the author mainly investigated the existing pick-by-vision solutions mainly using Google and Youtube with a similar set of keywords.

Findings from the literature will be included in the theoretical background in **Chapter 2**, and used as an input for the design and development of the pick-by-vision solution in **Chapter 3**.

### 1.2.2 The development of a pick-by-vision system

The design, development and implementation of a functional pick-by-vision system can be considered as the most time-consuming and the hardest phase of the present study. Engineered by Microsoft, the HoloLens can be considered as a wireless computer, containing its own processors and applications to be run for various purposes. To be able to benefit from its high capabilities, one must first design and develop an application or use the applications that have already been developed. However, there is no application available to public that is usable for order picking. The HoloLens has only been released 3 years ago, which could explain this observation. On one hand, as mentioned earlier, there are several private companies developing pick-by-vision applications to sell them to other companies. On the other hand, scientists who have researched on pick-by-vision systems have most of the time developed their own applications, without making them available to public. Developing an application has then become a necessity to conduct the present research.

A first idea was to get a hand on an existing application and then customize it to be able to test it in the logistics 4.0 laboratory. The supervisor of the present study has taken contact with some companies to purchase an existing pick-by-vision application but due to limited time, it will not be available before the end of the present thesis.

The other possibility was to reach out to the authors of Hanson et al. (2017), who agreed to share the application using a tunnel-based visualization they have developed. As

kit preparation activities are rather similar to order picking activities, adapting their application to suit the present work seemed to be a viable option. However, as the application was developed more than two years ago, the software for developing such an application (Unity) and the development toolkit provided from the mixed reality documentation (Microsoft, 2019b) underwent several updates. As a result, numerous bugs and errors in the application have arisen, making it impossible to use in the current state. Besides, given his study background, the author has limited computer programming skills. Thus, debugging the application and finding the correct code lines to tailor for the present study has proven to be very difficult and time-consuming, especially without the assistance of its creators who are currently working in Sweden.

It has then be decided to create a new pick-by-vision application with the Hololens from scratch. Before starting, knowledge about the necessary tools to build an Hololens app and competencies to use them correctly need to be acquired by the author. The development of the app itself has been an iterative process with multiple trial-and-error steps. The process of developing and designing of the present pick-by-vision application will be further described in **Chapter 3**.

### **1.2.3 The experimental research followed by a comparative analysis**

Since this paper aims to extend Battini et al. (2015)'s work, a possible approach is to get inspiration from their methodology. The authors did extensive observations of different picking systems over one month of in each of the studied industrial cases. According to the supervisor's experience, who is one for the co-authors of Battini et al. (2015), one of the methods was to use video recordings to analyze the picker's behaviour to determine precisely each of the individual time components contributing to the dependent picking time of each technology. Plus, the authors had the possibility to interview the warehouse managers to determine error probabilities.

Such methodology has not been suitable for the current thesis as extensive testing to estimate different parameters with video recordings analysis would take too much time. Accurate estimation of the error probabilities is also difficult to achieve without interviewing some warehouse managers. Consequently, to be able to conduct a relevant comparative analysis with other different order picking systems, several essential assumptions has been made and will be presented in **Section 6.1**.

However, what is feasible in this study is the estimation of the general dependent picking time of the developed pick-by-vision system (instead of each of the individual time components) thanks to the tests that took place in the logistics 4.0 laboratory. The experimental part of the thesis can be qualified as a quantitative method with the goal of answering to research question 2. Hanson et al. (2017) published their experimental research on the use of smart glasses for conveying picking information in kit preparation for the journal *Computers & Industrial Engineering*. As the journal is well-known for the quality of its publications and as order picking and kit preparation operations present multiple similarities, it is relevant to adopt a similar experimental approach here. The idea is to involve several test persons to perform order picking for a given number of picking

lists while timing their performance for each picking tour. An average picking time is then calculated from all the measurements. Schwerdtfeger et al. (2011) also carried out an iterative design process following a similar experimental approach in their study of designing an optimal visualization for a pick-by-vision system.

The proceeding and the circumstances of the experiment will be described in **Chapter 5**. Dependent picking time with the pick-by-vision system estimated from the measurements at the laboratory will then be used as an input for Battini et al. (2015)'s economic model to assess the considered picking system. An introduction to the employed economic model will be given in **Chapter 4**. Being one of the co-authors of Battini et al. (2015), the supervisor provided some insights into their research and gave some guidance about how the economic model should be used for the pick-by-vision system to include it in the comparison analysis with other picking systems they have conducted in their paper. For the sake of the flow of the paper, findings and their analysis and discussion will not be separated into two individual chapters "Results" and "Discussion", but merged into a single "Results and discussion" chapter. This means that in **Chapter 6**, the results from the economic model will be presented and analyzed at the same time, which brings the main answers for research question 3. Some sensitivity analyses are also conducted in **Chapter 6** to analyze the impact on the outcome from the variations of the input values of some parameters. With the research question 3 in mind, a qualitative assessment of the Hololens solution will also be included in the discussion. Finally, the conclusions as well as suggested limitations and further work are presented in **Chapter 7**.



# Theoretical background

Before diving into the pick-by-vision system, this chapter offers the theoretical background which is needed to understand what order picking activities consist of, along with an introduction to augmented reality.

De Koster et al. (2007) conducted a thorough literature review summarizing key theories in warehouse picking operations which will be used later on in this paper. Throughout the paper, both terms *warehouse picking* and *order picking* will be used, which both refer to "the process of retrieving products from storage (or buffer areas) in response to a specific customer request" (De Koster et al., 2007).

## 2.1 Warehousing fundamentals

First, as order picking operations take place in a warehouse, understanding the fundamentals of warehousing is important. In the past, a need in responsiveness to customers has been identified and has led to the establishment of warehouses in companies. The main purpose is to store or buffer products, e.g. raw materials, work-in-progress, finished goods etc., at and between the starting points and the points of consumption. As a consequence, warehousing leads to the emergence of different value-adding activities such as kitting, labelling, product or order assembly, customized packaging or palletization. Warehouses can also function as re-distribution center, allowing products, materials or product carriers to be recovered from customers and to be further distributed to other customers, manufacturers or recyclers (De Koster et al., 2007).

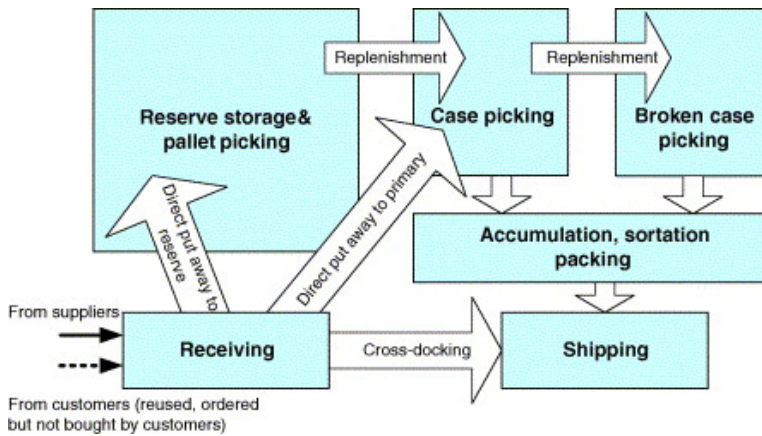
Lambert (1998) enumerated different missions to which warehouses contribute in a company. Some examples are:

- Achieving transportation economies
- Achieving production economies

- Taking advantage of quantity purchase discounts and forward buys
- Supporting the firm's customer service policies
- Meeting changing market conditions and uncertainties
- Providing temporary storage of material to be disposed or recycled
- Providing a buffer location for trans-shipments

As warehouse management and handling large inventories can be costly, some companies strive to reduce their need in storage by adopting different strategies such as lean manufacturing, virtual inventory or cross-docking. However, storage and buffer of raw materials, parts and products are still necessary for the majority of supply chains (De Koster et al., 2007).

The main activities in warehouses, as illustrated in **Figure 2.1**, consist of receiving, transfer and put away, order picking/selection, accumulation/sortation, cross-docking and shipping (De Koster et al., 2007).



**Figure 2.1:** Typical warehouse functions and flows. (Source: Tompkins et al. (2003))

The focus will from now on be more centered on order picking operations.

## 2.2 Warehouse picking operations

According to De Koster et al. (2007), order picking/selection is the major activity in most warehouses. It can be simply described as the process of "obtaining a right amount of the right products for a set of customer orders". In fact, several sub-activities are involved:

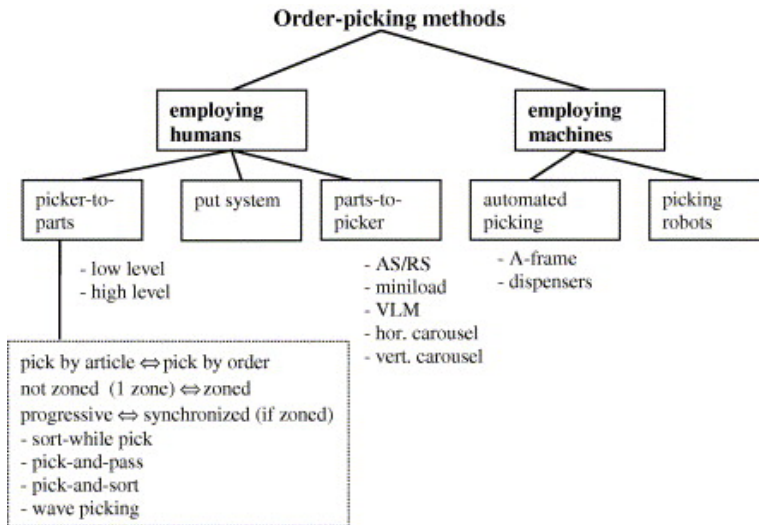
- Clustering and scheduling the customer orders
- Assigning stock on locations to order lines

- Releasing orders to the floor
- Picking the articles from storage locations
- Disposal of the picked articles

An order line (can also be referred as a picking row) corresponds to one unique product or stock keeping unit (SKU) in a given quantity and a customer order is made of one or multiple order lines. In this present paper, the focus is on picking the articles from storage locations, particularly on order picking systems, even though all the mentioned sub-activities are strongly interrelated.

### 2.2.1 Different order picking systems

Numerous picking systems exist and often several of them are adopted within one warehouse. **Figure 2.2** shows a classification of different existing warehouse picking systems depending on their strategies. The automated systems or the machine-employed systems are not of our interest in this paper.



**Figure 2.2:** Classification of different order picking systems. (Source: De Koster et al. (2007))

The *picker-to-parts* systems, where the operator travels along the aisles to pick articles, are the most commonly used in warehouses (De Koster et al., 2007). These systems can be further classified into two types: *low-level picking* and *high-level picking*. The low-level picking system implies that the picker travels along the storage aisles and picks directly from storage racks or bins. In high-level picking systems, high storage racks are used and the operator travels along the aisles using a truck or crane which stops in front of the pick location before he or she picks the right items. In this study, a low-level picker-to-parts

system is simulated in the laboratory to experiment the use of AR, but such technology can also be relevant in other types of picking systems.

In addition, several strategies can be distinguished within picker-to-parts systems. *Pick by order* (discrete picking), where the operator is focused on one customer order at a time, is opposed to *pick by article* (batch picking), where multiple customer orders are handled simultaneously by the operator. In the case of batch picking, the order picker can either adopt the *sort-while-pick* strategy, where the sorting is done immediately after the item is picked (placement on the picking cart), or the *pick-and-sort* strategy, where the sorting is performed once the pick is accomplished. *Zoning* is another picker-to-parts variant where the storage area is divided into several parts or 'zones' in a logical way with one order picker responsible for each 'zone'. The zoning can either be *progressive* or *synchronized*. In the first case, the orders are being passed from zones to zones for the pick to be completed. In the second case, the orders are being picked in parallel in the different zones. Orders for a common destination can be grouped in 'waves' when they are for example planned to be shipped at a given time with a given carrier. Operators then carry on picking the corresponding items in their zones until the current *picking wave* is finished, a next picking wave can only start after the previous one is completed. This strategy is called *wave picking* and is usually combined with batch picking.

The machine-employed alternatives to picker-to-parts systems are *parts-to-picker* systems. Parts-to-picker systems are semi-automatized and use automated storage and retrieval systems (AS/RS), e.g. aisles-bound cranes, that retrieve one or more pallets or bins and place them to the pick position. *Put* systems can be described as an extension of picker-to-parts or parts-to-picker systems where the items are first retrieved with either picking strategy and then further distributed over customer orders (the products are "put" in customer cartons).

De Koster et al. (2007) pointed out a paradox where substantial research has been done for AS/RS systems whereas only little literature has focused on manual picking, which accounts for the majority of picking operations (80% in western Europe according to the authors' experience).

In this paper, only the pick by order strategy from a picker-to-parts system is of interest, as the study is centered on the impact of the choice of a given picking system, and not the impact of the adoption of a given picking strategy. The other picking strategies such as pick-while-sort, progressive zoning and so on, are only mentioned here without being further discussed.

## 2.2.2 Order picking objectives

According to Goetschalckx and Ashayeri (1989), the most common objective of order picking systems is "to maximize the service level subject to resource constraints such as labour, machines, and capital". Order delivery time, order integrity and accuracy are the main factors that describe the service level. De Koster et al. (2007) emphasizes on the speed with which an order is retrieved that links order picking and service level. "The faster an order can be retrieved, the sooner it is available for shipping to the customer".

Travel is a major component in order picking activities, but it is considered as a waste since it costs labour hours without adding value (De Koster et al., 2007). As a result, minimizing the travel distance (which is the same as minimizing the travel time) is one of the primary objectives. Subsequently, to measure the performance of the picking activities, average travel distance and the total travel distance are the two measures that are generally used in the literature.

More in line with the research direction of the present paper, minimizing the total costs is another important objective of an order picking system. The latter comprises the investments and the operational costs.

De Koster et al. (2007) also enumerated some other examples of objectives that are often taken into account during the warehouse design and optimization process such as minimizing the throughput time of an order, maximizing the use of space, labour and equipment, maximizing the accessibility to all items etc.

### 2.2.3 Factors affecting the design of an order picking system

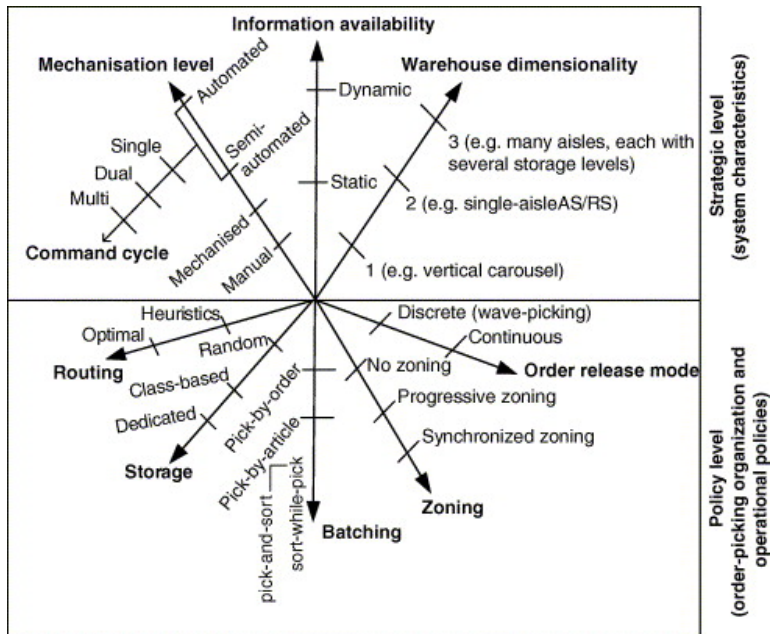
According to De Koster et al. (2007), order picking system design choices are complex because these are impacted by various internal and external factors. Marketing channels, customer demand pattern, supplier replenishment pattern, inventory levels, the overall demand for a product and the state of the economy are the main examples of external factors listed by Goetschalkx and Ashayeri (1989). System characteristics, organization and operational policies of the order picking system are considered as the internal factors. System characteristics refer to mechanization level, information availability, and warehouse dimensionality. Routing, storage, batching, zoning and order release mode are the five factors describing the organization and operational policies. **Figure 2.3** gives a visualization of the internal factors that illustrate the complexity of order-picking systems. The further a system is placed from the origin of the figure, the more complex it is and the harder it is to design and control.

To achieve the mentioned objectives in the previous section, companies make crucial design and control decisions at different levels (tactical and operational), with different time horizons, which are greatly interdependent. Accordingly to the factors just mentioned, here is a list of the common decisions given by De Koster et al. (2007):

- Routing: defining the routing policy of the order picker, i.e. the itinerary the picker follows during the picking tour (operational level)
- Storage: assigning products to storage locations (tactical and operational level)
- Batching: assigning orders to pick batches, i.e. gathering several orders in one picking tour (tactical and operational level)
- Zoning: dividing the picking area into work zones by grouping aisles (tactical and operational level)
- Order accumulation/sorting: if batching and/or zoning is applied, the picked units (gathered in batches) need to be sorted back to individual customer orders or delivery

destinations (operational level)

- Layout design and dimensioning of the storage system (tactical level)



**Figure 2.3:** Complexity of order picking systems. (Source: Goetschalckx and Ashayeri (1989))

The layout of a given warehouse significantly impact the picking time as it directly influences routing (De Koster et al., 2007; Battini et al., 2015). But to study this impact of layout on a given order picking system, one has to measure the performance of the order picking system in different layouts of a same warehouse. As it is not the objective of the present study, the influence of layout will not be addressed in this paper.

Likewise, the explanation of the other different factors will not be further extended, but the reader should keep in mind that they strongly affect the design of an order picking system. Reciprocally, the implementation of an order picking systems will influence the routing policy, the storage assignment and so on, which is why all of these different aspects should be addressed at the same time in the warehouse design phase. For this particular research, the focus is on the economic evaluation of a particular order picking system. As addressing different issues concerning the different factors is a very complex task, the latter will be given less attention for the rest of the paper.

## 2.2.4 Order picking process

Order picking can be simply described by the following general scheme: getting information, searching, picking and confirming (Battini et al., 2015). Depending on the adopted

order picking system, this working scheme may vary, e.g. getting information and searching are merged into one single phase or picking and confirming are taking place simultaneously etc. Working schemes of different picking systems will be shown later on in **Section 4.1**. Schwerdtfeger et al. (2011) divides order picking in two phases: the coarse navigation in which the operator travels and finds the correct shelf and the fine navigation in which the operator has to find the specific box or bin to pick from. The time during which the picker "interprets and understands the order as a 3D navigation and picking task" can be referred as the dead time (in other words, the getting information and the search steps mentioned above) and it is the only time component that can be optimized with a pick-by-vision solution according to Schwerdtfeger et al. (2011).

During the picking process, errors of different kind can emerge, and they can be classified into two categories. The first type is a *detectable error* that can be easily identified and allows the picker to bring immediate correction actions. The second type refers to *propagating errors* which are only recognizable at the end of a given picking tour, resulting in more time and effort to rectify. **Table 2.1** gives the description of the four types of potential errors during a picking tour, as well as the corresponding correction actions (from Battini et al. (2015)). The correction actions would require a picker to spend the time they would use for actual picking if the errors did not occur. Hence, picking errors can be translated into costs from this perspective.

**Table 2.1:** Different potential errors during a picking tour

Type	Notation	Description	Following actions
Detectable	$e_1$	Right item picked but wrong item confirmed	Confirmation of the right picked item
	$e_2$	Wrong item picked and wrong item confirmed	Wrong item stocked and right item picked
Propagating	$e_3$	Wrong item picked but right item confirmed	At the end of the picking tour, wrong item stocked and right item picked
	$e_4$	Wrong quantity picked	At the end of the picking tour, extra item stocked or picked

## 2.3 Augmented reality

As mentioned in the **Section 2.2.2**, minimizing the order picking time is necessary to achieve the desired service level. In this regard, the AR technology has a potential to bring significant improvements. First, a short introduction to AR will be presented.

### 2.3.1 Generalities

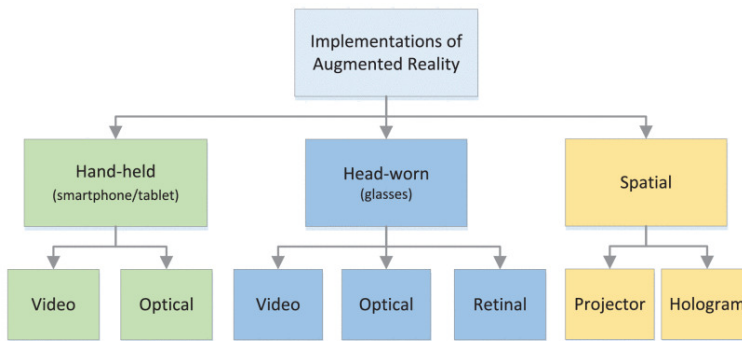
*Augmented Reality* is the concept of enhancing the human's perception of reality by overlaying virtual elements on the real worldview (Syberfeldt et al., 2017). As of today, it is widely applied in various fields such as gaming, sport and tourism, targeting mainly

entertainment.

Azuma (1997) defines augmented reality as any system that gathers the three following characteristics:

- it combines the real world elements with virtual elements
- it is interactive in real-time
- it is registered in 3D dimensions

As a result, AR is not only restricted to head-mounted displays (HMD). Likewise, it is intuitive to associate AR with only overlaid visual information, but it has actually the potential of covering the other senses such as hearing, touch and smell. Syberfeldt et al. (2017) provides a classification of diverse potential devices paired with AR which shown in **Figure 2.4**.



**Figure 2.4:** Different devices and optics used in augmented reality. (Source: Syberfeldt et al. (2017))

In **Figure 2.4**, several employed optics are mentioned, here are their definitions (Syberfeldt et al., 2017):

- Video: Real and virtual worlds are merged into the same view for the user which is completely digital here
- Optical: Virtual elements are overlaid directly on the view of the real world
- Retinal: Low-power laser light technology is used to project virtual elements are projected directly onto the user’s retina
- Hologram: Holograms are shown in the real world using a photometric emulsion that records interference patterns of coherent light
- Projection: The use of a digital projector is required to project virtual elements onto the real world

It is important to distinguish AR from *Virtual Reality* (VR), where the user is totally immersed in a virtual world, unable to see the real world around him/her. The middle



ground between both concepts is *Mixed reality*. Pan et al. (2006) defines it as "the incorporation of virtual computer graphics objects into a real three dimensional scene, or alternatively the inclusion of real world elements into a virtual environment. The former case is generally referred to as augmented reality, and the latter as augmented virtuality".

The smart glasses model on which this study is built is the HoloLens, developed by Microsoft. The HoloLens has the ability of displaying high definition holograms and to anchor them in the real world surroundings. It is therefore often referred to as an MR technology. But for the sake of simplicity, distinction between MR and AR will not be mentioned further in this paper. We will also center the focus on smart glasses from now on.

### **2.3.2 Smart glasses**

In the recent years, the potential of assisting operators with smart glasses in diverse industrial activities such as assembly, maintenance, quality control or material handling has been identified and explored. A number of recent studies have reported promising results in terms of gain in both productivity and quality (Syberfeldt et al., 2017).

A definition of smart glasses given by Syberfeldt et al. (2017) is "a head-up transparent transparent display integrating a wearable miniature computer that adds virtual information to what the user sees". The information is presented at eye-level by the hands-free device, which makes the smart glasses an ideal tool to assist operator in an industrial context. Besides, with integrated cameras, the glasses can detect and recognize the elements the user is looking at, allowing them to provide context-aware information (Syberfeldt et al., 2017). Hence, the user can receive the needed information at the right time and place, while focusing on his/her original tasks.

In the present paper, the studied model is the HoloLens, which is equipped with a microphone and speakers allowing the user to vocally interact with the device and to benefit from spatial sound effects. The HoloLens is also capable of spatial mapping thanks to its multiple integrated cameras and sensors (Microsoft, 2019b).



# Chapter 3

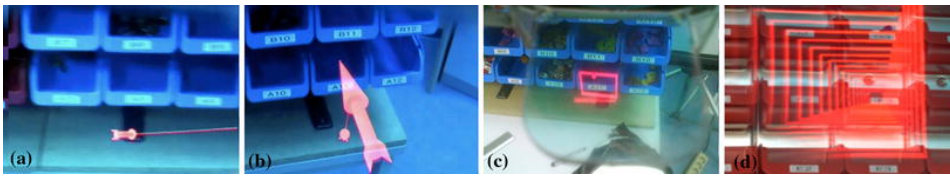
## The pick-by-vision solution

This chapter aims to bring some key elements to answer research question 1. It will also show the design choices the author has made for the developed pick-by-vision system.

### 3.1 Literature study

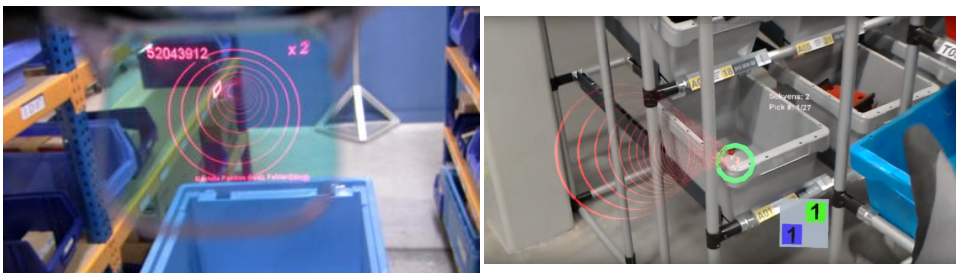
Schwerdtfeger et al. (2011) conducted a thorough step-by-step learning-by-trying study in the design of an efficient pick-by-vision solution. They first designed several potential visualization and then carried out some experiments with random test persons to measure picking times and errors and to collect feedback about the user experience. It was an iterative process where the experiments supported the decision to chose one or two best solutions among the alternatives, which are then further improved with new designed alternatives that are again subject to experiments and so on. Their experiments were first carried out in a laboratory setup, then in an industrial environment. They have shown that designing a functional picking system, especially with innovative technology such as head mounted display can be very complex, and that different designs can lead to very different picking performances.

From their extensive research, Schwerdtfeger et al. (2011) have determined a visualization that they judged to be optimal, which is based on a guiding tunnel which shape looks like a "flexible hose of a vacuum cleaner", pointing at the next to-be-picked item (see **Figure 3.2a**). The tunnel-based visualization is able to indicate to the user whether he/she is getting close to the item or not, thanks to the bending of the curve. Examples of the different prototyped visualizations from Schwerdtfeger et al. (2011) research are shown in **Figure 3.1**.



**Figure 3.1:** Examples of different tested pick-by-vision visualizations: a. The meta visualization b. The arrow-based visualization c. The frame-based visualization d. The tunnel-based visualization. (Source: Schwerdtfeger et al. (2011))

Based on these findings, Hanson et al. (2017) developed a tunnel-based solution with the Hololens for kit preparation for mixed-model assembly, which differs slightly from order picking operations. **Figure 3.2b** shows the implemented visualization in the Hololens.



**(a)** Schwerdtfeger et al. (2011)'s optimal visualization. **(b)** Hanson et al. (2017)'s visualization for kit preparation.

**Figure 3.2:** Two examples of the tunnel-based visualization.

One should bear in mind that Schwerdtfeger et al. (2011) conducted their research more than 8 years ago and they have most of the time worked with a Nomad HMD. This model was considered as providing very high see-through capabilities at that time and augmented the vision only for one eye. During the elapsed 8 years, many innovations have emerged in the AR field and respective technological capabilities have significantly increased. This means that an optimal pick-by-vision designed at that time might be sub-optimal today. Likewise, it may be worthy to re-consider pick-by-vision designs that have been proven inefficient with the technology of the past, because of bigger field of view or better rendering, for example.

Guo et al. (2014) also carried out a comparative study between pick by Head-Up Display (HUD), pick by Cart-Mounted Display (CMD), pick-by-light and pick-by-paper. The pick-by-HUD which offers a static 2D visualization of the picking location and quantities has proven to be more efficient than the other compared picking systems. This work was extended in Wu et al. (2016) where the authors have introduced an error detection system based on weight checking.

Syberfeldt et al. (2017) proposed a set of guidelines for decision makers to make the

most appropriate investment of smart glasses for their uses in an industrial environment. In the same study, a review of the available products was also performed. With a similar objective to the present paper, this study focused more on the characteristics and capabilities of the smart glasses and did not address specific activities such as order picking.

Stoltz et al. (2017) researched on the opportunities and the barriers for the AR applications in warehouses. For this purpose, the authors conducted semi-structured interviews with solution providers, warehouse managers, logistics and AR experts to gain insight about the current situation and the expectations from such technologies. Empirical study with an Google Glass application for the sorting process was also conducted to collect feedback and to identify potential issues and benefit with the practical using the AR technology. In line with this study, reduced error rate and increased working speed are among the identified expected benefits for using smart glasses in warehouse operations. Some of their findings will be reminded in the discussion in **Section 6.4**.

Outside the literature, there are several pick-by-vision systems, developed by some companies specialized in digitalization of operations, which are sold as logistics solutions in the market. Some examples are Itizzimo (2013), DHL (2015), Picavi (2015), Scandit (2018), LUCA Logistic Solutions (2016) or Joinpad (2017). These solutions show different types of visualization using arrows, frames, rectangles or simple text display, which could be used as inspiration sources for developing our own pick-by-vision application. However, as most of these videos have a commercial purpose, they might have undergone some video editing treatment to make the technology look more attractive, which might deviate from the real experience. The actual performance of some of the mentioned pick-by-vision systems could in fact be questionable.

As mentioned in the introduction, there has been an attempt to build up a customized pick-by-vision application from Hanson et al. (2017)'s solution. Unfortunately, it has not led to a functional application and any material from their project has been hardly reusable. Therefore, a new pick-by-vision application in the Hololens has been developed from scratch, which will be presented in the following sections.

## **3.2 Development of the pick-by-vision solution**

Stoltz et al. (2017) identified computer programming as one of the barriers for using AR in warehouse operations. Since the programming environment and language are not standardized, it is difficult for users to experiment with the hardwares, to develop their own softwares and to link devices with existing systems.

Applications on the Hololens are developed using the cross-platform game engine, Unity. In the development phase, components of the Hololens application are being managed by Unity in a virtual 3D environment as gameobjects. The interactions with these gameobjects and their behaviours are dictated by scripts written in the C# programming language. Before diving in programming, an essential first step is to learn how the game engine works and to learn coding in the c# language. For this purpose, tutorials on Youtube as well as developer forums have been extensively utilized. Another valuable source of in-

puts is the Mixed Reality documentation website (Microsoft, 2019b) with information that is continuously updated by the contributors. In addition to programming advice, best practices, solutions to common problems and so on, Microsoft (2019b) also provides an open source development kit for Holograms applications containing the necessary tools facilitating the work of programmers, known as the Holokit or the Mixed Reality toolkit.

Then, the development per se of the pick-by-vision application has been an iterative process. The Hologram application underwent several designs, whose inspiration came from the literature study, before reaching the current version. Code lines were first written on paper before being translated in c# scripts. The play mode in the unity editor that allows the developer to test the application with the glasses was then used to debug the newly created application. Upon detected bugs or implemented functionalities that turned out to be not so useful, the code has been revised before being tested in the Hologram again. Some usable codes have been retrieved from open-source platforms and integrated in the application, such as the barcode functionality from Taulty (2016).

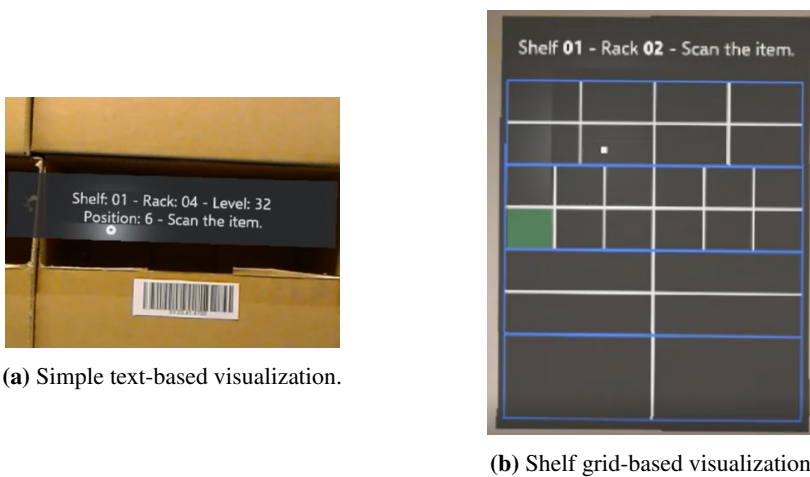
Finally, the developed pick-by-vision solution is an application to be deployed from the computer to the Hologram via Visual Studio (an integrated development environment (IDE) from Microsoft). After being deployed for a first time, the app can be run on the Hologram without being remoted by a computer.

### 3.3 Design of a pick-by-vision solution

As explained earlier, picking performance is directly affected by the way a pick-by-vision system has been designed. In other words, the gain in productivity (compared to the traditional pick-by-paper) varies depending on what picking information is shown on the glasses and how it is shown, which is very important to take into consideration when evaluating the profitability of a given pick-by-vision system. The literature study showed that the design possibilities are numerous, and this section aims to explain to the reader the design choices that were made, i.e. the different features that the developed pick-by-vision solution includes. To get a better understanding and a visualization of the application in practice, the reader can watch the explanatory video made by the author accessible with the link: [https://www.youtube.com/watch?v=rBW\\_Y8xUeE0](https://www.youtube.com/watch?v=rBW_Y8xUeE0) One should keep in mind that the application is not running in the video as smoothly as in reality, because it uses its cameras to record the footage in addition to running the pick-by-vision application at the same time.

#### 3.3.1 The visualization in the glasses

According to the findings in **Section 2.2.4**, a picking system is supposed to assist the operator in the four phases of picking: getting information, searching, picking and confirming. Schwerdtfeger et al. (2011) highlighted that the dead time or the getting information phase is where AR has the most potential to optimize in a picking process. Schwerdtfeger et al. (2011) also pointed out the problem of obtrusive visualization when using head mounted



**Figure 3.3:** Two tested types of visualization for the pick-by-vision system.

display for order picking. Working in an industrial environment, it is important that the operator is able to see his/her surroundings clearly as he/she needs to interact with the real environment and can be exposed to some dangers. Hence, it is crucial to show the picking information to the picker in a very intuitive, comfortable way (Stoltz et al., 2017), as well as having a minimalist solution, not to obstruct the user's view too much. An efficient visualization will also reduce the need for an extensive training to learn how to use the system, which is valuable (Andriolo et al., 2013; Schwerdtfeger et al., 2011).

The first design of the present pick-by-vision solution was to only display text information related to the item's location, as shown in **Figure 3.3a**, which relies on the interpretation of the user to find the correct item location. This first version is inspired by Picavi (2015). Then, to make the solution more intuitive, the design switched to displaying only the shelf number and the rack number in text, complemented with a grid that replicates the corresponding rack where the to-be-picked box is highlighted with a green blinking box. Such a decision was taken following the recommendations from the supervisor and the co-supervisor. It was also partly inspired from the frame-based visualization from Schwerdtfeger et al. (2011)'s research which have reported to show good results, the visualization from Guo et al. (2014), as well as the visualization from DHL (2015). **Figure 3.3b** shows the visualization of the present pick-by-vision solution.

Schwerdtfeger et al. (2011) reported that visualizations being not consistent enough can leave the user confused, which leads to more errors, e.g. the arrow based visualization from Schwerdtfeger et al. (2011) (49 errors recorded over 2754 items picked). With such a design, the benefit from having a very simple display instead of more complex visualizations is that a little interpretation effort is left to the user, preventing the user from misunderstanding the guidance from the visualization that potentially leads to a wrong location.

As shown in **Figure 3.3**, the picking information is attached to a virtual blackboard

that seems to be floating. One can see in the explanatory video (Schan, 2019) that the blackboard is not "locked" in the center of the user's field of view. A visualization which is locked in the center of the field of view may seem to be the simplest and most intuitive solution, but it is likely to cause visual discomfort according to the experience of some users and developers (Uzun, 2018; Windows Mixed Reality Developer Forum, 2016). A display locked blackboard visualization has been tried and the result appeared to be shaky and twitchy, but also obstructing since always in the middle of the field of view.

In order to solve this visual comfort issue, billboard and tag-along concepts have been applied to the blackboard. Billboarding allows a given hologram (i.e. the blackboard here) to always be facing the user, only by forcing it to rotate on itself when needed (Microsoft, 2019b). Tag-along objects are objects that are always "a glance away" from the user's gaze, while the user moves in the real-world environment. "As the user moves, the content will attempt to stay within the users periphery by sliding towards the edge of the view. Depending on how quickly a user moves, it may leave the content temporarily out of view. When the user gazes towards the tag-along object, it comes more fully into view" Microsoft (2019b).

These two concepts provide the desired visual comfort by enabling the blackboard to always have a stable display (not shaky), to not obstruct the field of view (by staying at the sides when desired), and to be immobile when stared at. Moreover, according to Microsoft (2016) holograms are most comfortable at distance = 2m. Under 1m, it gets really uncomfortable for the user and above 2m it causes slight discomfort. This has been taken into account when toggling the parameters of the tag-along blackboard.

### 3.3.2 The confirmation phase

In the literature, the confirmation phase of a pick-by-vision system is often given only little attention to. For instance, the wizard of oz technique (where the picker says "I picked it") or a buzz button has been used in Schwerdtfeger et al. (2011) to proceed to next item without product confirmation. Likewise, in Hanson et al. (2017), the keyword "next" was used and recognized by the HoloLens to switch to next product's location. Without confirmation, picking speed might be increased, but picking errors may also arise although they could be easily avoided. Wu et al. (2016) proposed a confirmation method by checking the weight of the picked items once it is put on the picking cart. The error detection was indeed fully functional but the errors are detected once the items are on the cart, making correction actions time-consuming and difficult.

According to Stoltz et al. (2017), barcode scanning with smart glasses is not as functional as with smartphone cameras or commercial barcode scanners, and is therefore not recommended. Paradoxically in the same study, it has been stated that a fast and accurate barcode reader would be a crucial feature for a successful AR solution according to the interviewed participants. To the author's knowledge and according to Stoltz et al. (2017), there is no example of combination of barcode scanning with a pick-by-vision system in the literature. Nonetheless, in the market, some companies seem to have successfully implemented the barcode scanning functionality with the HoloLens (Picavi, 2015; Scandit,



2018). Besides, from research in the AR developers community, barcode and QR scanning with the Hololens is possible and seems to be working fine with open-source programs that are available publicly. It has then been decided to integrate barcode scanning as one of the features of the present pick-by-vision system.

A barcode scanning system has then been successfully implemented inside the hololens solution. This enables the picker to confirm that he/she is picking the correct item by placing the item in front of the glasses within a distance about 50cm, but also to be alert when picking the wrong item. Contrary to Wu et al. (2016), when a wrong item is physically picked, the error is immediately detected with a wrong scan before being stored on the cart and while the picker is still facing the wrong location, allowing the picker to directly put the wrong item back to where it belongs, which is less time-consuming and more handy.

The Hololens cameras are continuously looking for barcodes and upon a detected scan, the integrated speakers play either a validation or an error sound to guide the picker. The displayed text also takes the colour green or red accordingly. The integration of such sound and color system is important to help the picker understand the right information and make the solution more intuitive (Battini et al., 2015). The pick-by-vision system then acquires a significant advantage by benefiting from the confirmation phase without requiring the extra use of hands again.

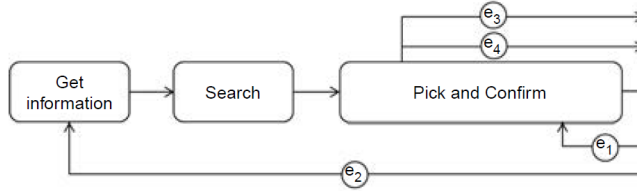
To ensure that the user has understood the displayed information, the application waits for his/her response by using the paired clicker or by air-tapping (see Schan (2019)). It can be argued that the use of a clicker requires the use of one hand, but it is indeed small enough not to prevent the picker to use both hands to pick. The clicker comes with a rubber band, enabling the picker to wrap it around his/her finger in a comfortable way (it could be lying against the knuckles instead of remaining inside the hand for example) and not to lose it.

Another important design decision which has been made is that the Hololens application does not request the picker to scan all the picked items from a same order line, but only the first item. The to-be-picked quantity is displayed upon a correct scan. If the picker has to scan for every SKU he/she picks, it would increase considerably the picking time. In the current scenario, if the first scan is correct, the picker should already be familiar with the correct stock location, thus picking from the same box should not be a source of picking errors. Moreover, the blackboard keeps displaying the same location until the picker proceeds to the next pick.

Schwerdtfeger et al. (2011) stated one of the weaknesses of their solution was that it did not prevent the user from skipping an order line when the user presses the confirm button twice for example. Their application did not allow the user to go back to the previous picking order, which had led to more picking errors as a result. In the present solution, the same issue can also occur if the picker clicks too fast right after scanning the correct product. In this case, he/she might have missed the quantity information, as the application is already showing the visualization for the next pick. A solution here was to allow the user to say the keyword "go back" that will command the system to display the previous rack, the previous box to pick from and the previous quantity.

With the integrated barcode scanning feature, the working scheme of the considered

pick-by-vision is as indicated in **Figure 3.4**. One can notice that it is the same working scheme as the voice-picking system, which will be presented in **Section 4.1**. The particularity of this working scheme is that the physical pick and the confirmation take place simultaneously, preventing error type  $e_1$  from occurring (see **Section 2.2.4**).



**Figure 3.4:** Working scheme of the considered pick-by-vision system with corresponding errors.

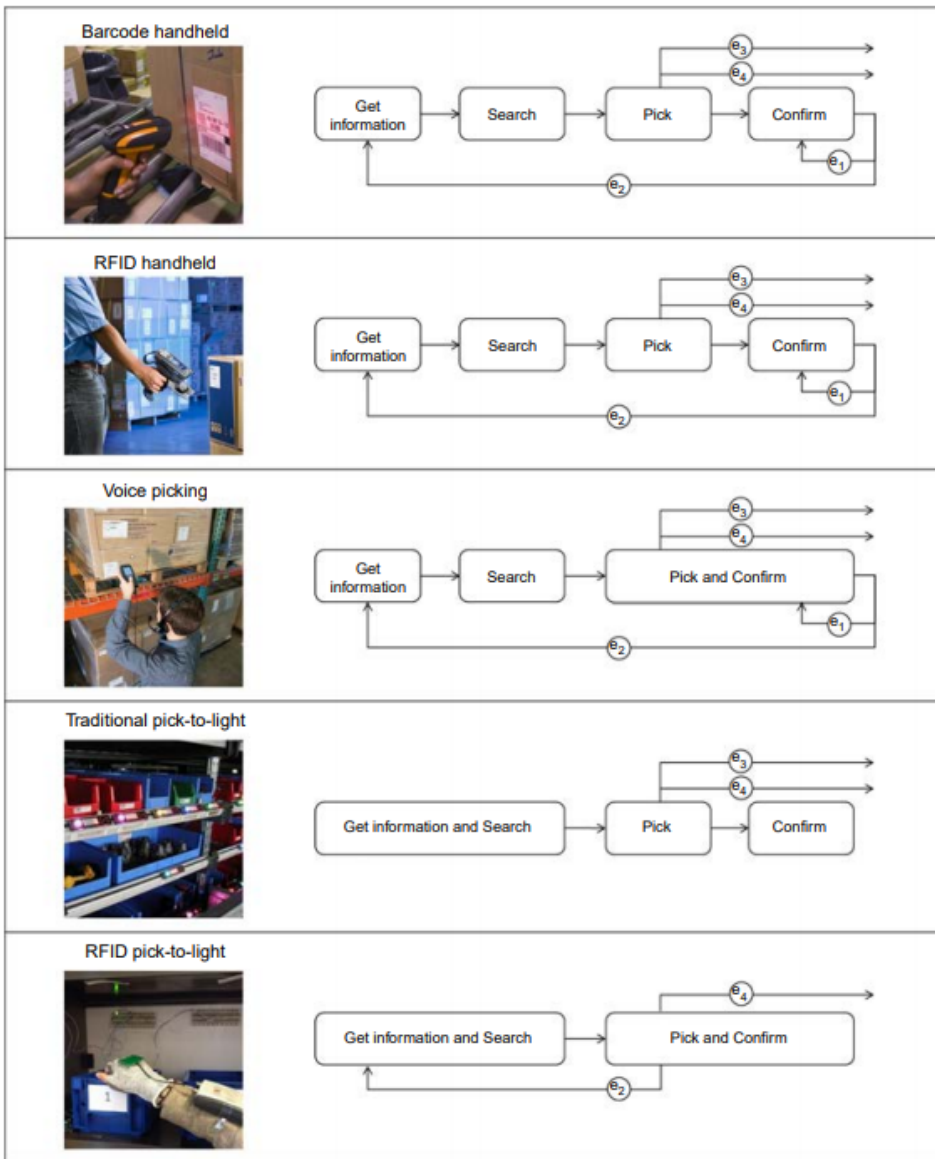
# Introduction to the economic model

As mentioned in **Section 2.2.2**, the main objective of order-picking is "to maximize the service level subject to resource constraints such as labour, machines, and capital". Adopting different order picking strategies or technologies may achieve different service levels and involves different resource constraints. In this chapter, different picking systems that are included in the comparison will first be described before the presentation of the economic model introduced by Battini et al. (2015).

## 4.1 Description of different picking systems

The most traditional way of order picking was picking products using printed papers (Battini et al., 2015; Hanson et al., 2017) as stated in the introduction **Chapter 1**. Battini et al. (2015) conducted a comparison between different paperless picking systems and gave the following definition for a paperless picking system: "A paperless picking system is constituted of a set of devices designed and adopted to facilitate the work of the operators, mostly in terms of getting information on the product to be picked and finding the corresponding storage location". As the main objective of the present paper is to extend the work of Battini et al. (2015), their main findings will be presented here, as well as the picking systems on which they have researched on, e.g. barcode handheld scanner, RFID handheld scanner, pick-by-voice, traditional pick-to-light and RFID pick-to-light. Since these are the five systems that have been assessed with the economic model, other existing picking systems will not be presented here, nor included in the comparative study.

According to Battini et al. (2015), the respective working schemes with potential picking errors (see **Section 2.2.4**) to the different picking systems are shown in **Figure 4.1**.



**Figure 4.1:** Working schemes with potential picking errors of the different picking systems. (Source: Battini et al. (2015))

### 4.1.1 Barcode handheld scanner

One of the first devices to be developed and adopted by warehouse managers is the barcode handheld scanner. As it is one of the features of the presented pick-by-vision, the picking

scheme is rather similar. Either all the items (SKUs) or all the storage locations are tagged with a barcode which the picker has to scan when picking the corresponding item. The use of this device is usually combined with the use of paperlist, but the picking list can also be displayed on the scanner for the most advanced models with an integrated screen that shows information about the next item to be picked (Battini et al., 2015).

### **4.1.2 RFID handheld scanner**

More recently, the radio frequency identification scanners and tags, with a similar operating principle as the barcodes, emerged and gained popularity in many logistics applications. The success of such technology relies on the higher reading speed, the possibility of reading from longer distances as well as the possibility of reading multiple tags at the same time (Battini et al., 2015).

### **4.1.3 Pick-by-voice**

Voice picking can be referred to as a poka-yoke (meaning mistake-proof in Japanese) system, and the goal is to prevent mistakes from happening. In this picking system, the picker wears a headset equipped with a microphone with which he/she interacts. Connected to the warehouse management system, the picker receives instructions about the pick (location and quantity) from the headset and confirms his/her pick verbally, by reading the four last digits on the barcode of the item for example, back to the system before moving on to the next pick (Battini et al., 2015).

### **4.1.4 Pick-by-light**

Another example of poka-yoke system is the pick-by-light system. The warehouse first has to equip light systems on its shelves. A light system is allocated to each stock location and is turned on when the corresponding product has to be picked by the operator. To indicate that a pick has been performed, the picker presses on the button located on the light system. This picking system can be complemented with a barcode handheld scanner. If several pickers are working in the same picking area at the same time, each picker needs to be paired up with a picking list, on paper or digital display, so that he/she can distinguish which lights correspond to his/her orders (Battini et al., 2015).

### **4.1.5 RFID Pick-by-light**

The last picking system included in the comparison is the RFID pick-by-light introduced in Andriolo et al. (2013), which is an extension of the traditional pick-by-light system. Such a system relies on the use of an RFID glove, which does not prevent the operator from using both hands. The passive RFID tags are then attached to the racks, which are also equipped with a set of different coloured lights. Different colours correspond to different picking

lists that are handled by different pickers if they are working simultaneously. Upon the physical pick of an item, the passive RFID tag is automatically read by the glove. Using wifi connection, the gloves communicates with the centralized control system which is able to turn the lights on and off. Errors are also minimized as they are detected when the glove reads a wrong tag. A combination of visual and acoustic signals warns the picker when wrong picks are performed Battini et al. (2015).

## 4.2 The economic model

The five picking systems presented above has been compared in Battini et al. (2015)'s study using the economic model introduced in the same paper. As the present paper aims to extend this comparison, some explanations about the economic model will be given. The economic model is translated in an hourly cost function for each picking system that includes four main hourly cost components:

- Hourly cost related to the stock locations  $C_{h,SL}^j$
- Hourly cost related to the workforce  $C_{h,P}^j$
- Hourly cost related to the picking errors  $C_{h,E}^j$
- Hourly fixed cost  $C_{h,F}^j$

The hourly cost function  $C_h^j$  can then be written as following:

$$C_h^j = C_{h,SL}^j + C_{h,P}^j + C_{h,E}^j + C_{h,F}^j \quad (4.1)$$

The equation can be written more explicitly as following:

$$c_h^j = \frac{n_{SL} \cdot c_{SL}^j}{h_{SL}} + \left( c_{h,P} + \frac{c_{d,P}^j}{h_{d,P}} \right) \cdot \left\lceil \frac{n_R}{\hat{p}^j} \right\rceil + c_E^j \cdot n_R + \frac{c_F^j}{h_F} \quad (4.2)$$

**Table 4.1** summarizes the different parameters and their notations.

**Table 4.1:** Parameters and notations in the hourly cost function. (Note: <sup>a</sup> Variable depending on the considered system j) Source: Battini et al. (2015)

Cost component	Expression	Notation	Description	
Stock locations hourly cost	$C_{h,SL}^j$	$\frac{n_{SL} \cdot c_{SL}^j}{h_{SL}}$	$c_{SL}^j$ [€/unit] $n_{SL}$ $h_{SL}$ [h]	Stock location unitary cost <sup>a</sup> Number of available stock locations Stock location devices total usage hours
Picker hourly cost	$C_{h,P}^j$	$\left( c_{h,P} + \frac{c_{d,P}^j}{h_{d,P}} \right) \cdot \left\lceil \frac{n_R}{\hat{p}^j} \right\rceil$	$c_{h,P}$ [€/h] $c_{d,P}^j$ [€] $h_{d,P}$ [h] $n_R$ [rows/h] $\hat{p}^j$ [rows/h]	Picker hourly cost Picker devices cost <sup>a</sup> Picker devices total usage hours Number of requested picking rows per hour Picking rate <sup>a</sup>
Picking errors hourly cost	$C_{h,E}^j$	$c_E^j \cdot n_R$	$c_E^j$ [€/unit] $n_R$ [rows/h]	Error unitary cost <sup>a</sup> Number of requested picking rows per hour
Fixed hourly cost	$C_{h,F}^j$	$\frac{c_F^j}{h_F}$	$c_F^j$ [€] $h_F$ [h]	Fixed costs <sup>a</sup> Fixed elements total usage hours

The picking rate  $\hat{p}^j$  is referred to the number of performable picks per unit of time, inversely related to the total picking time of one row  $t_{tot}^j$ :

$$\hat{p}^j = \frac{1}{t_{tot}^j} \quad (4.3)$$

If the number of requested rows per hour  $n_R$  is increasing above a certain threshold, the current workforce may not be able to keep up a satisfactory picking pace to fulfill the demand from the customer orders. The company will then need to hire an extra operator along with an extra necessary set of equipment (a picking cart plus the required devices depending on the picking system). This explains the use of the ceiling function in **Equation 4.2**, which rounds up the fraction to the next nearest integer.

The total picking time of one row  $t_{tot}^j$  can be split into two components: the travel time  $t_{trav}$  and the net picking time  $t_{net}^j$ . Contrary to the former which merely depends on the warehouse's layout and the routing policy, the latter is dependent on the considered picking system and can be further split into four components, corresponding to the four phases characterizing the working scheme (see **Section 2.2.4**):

$$t_{tot}^j = t_{trav} + t_{net}^j \quad (4.4)$$

$$t_{net}^j = t_i^j + t_s^j + n \cdot t_p^j + t_c^j \quad (4.5)$$

$t_i^j$ ,  $t_s^j$ ,  $n \cdot t_p^j$  and  $t_c^j$  correspond to the time needed for getting information, the search time, the actual pick time and the confirmation time respectively. Since in one order line, the picker might be solicited to pick several units from one product, the actual pick time is equal to the number of picked items  $n$  times the actual pick time for one unit  $t_p^j$ . Each of these individual time components varies from one picking technology to another: the information time and the search time depend on how well the picking system assists the operator in understanding the order requirements and finding the corresponding location, the actual picking time depends on whether the picker can use both hands and the confirmation time depends on the way the picker has to confirm (by voice, by scanning the item, by pressing a button etc.).

As mentioned in **Section 2.2.4**, picking errors can be translated into costs. In this economic model, the error unitary cost  $c_E^j$  is calculated by multiplying the probabilities of occurrence of each type of error  $p_{e_i}^j$  with the corresponding time required to bring the necessary correction action  $t_{e_i}^j$ . The sum of the four terms related to the four types of errors is then multiplied by the picker hourly costs  $c_{h,P}$  as follow:

$$c_E^j = c_{h,P} \cdot \sum_{i=1}^4 p_{e_i}^j \cdot t_{e_i}^j \quad (4.6)$$

The hourly cost related to error in **Equation 4.2** is obtained by multiplying the error unitary cost with the number of requested rows per hour. Again, the correction actions corresponding to each type of error depend on the considered picking system, as the working schemes differ from one technology to another. **Table 4.2** summarizes these different time factors for the five picking systems presented above.

**Table 4.2:** Time factors corresponding to each error type for different order picking systems. (Source: Battini et al. (2015))

	$t_{e_1}^j$	$t_{e_2}^j$	$t_{e_3}^j$	$t_{e_4}^j$
Barcode handheld	$t_c^j$	$2 \cdot t_{net}^j$	$2 \cdot t_{net}^j + t_{trav}$	$t_{tot}$
RFID handheld	$t_c^j$	$2 \cdot t_{net}^j$	$2 \cdot t_{net}^j + t_{trav}$	$t_{tot}$
Pick-by-voice	$t_c^j$	$2 \cdot t_{net}^j$	$2 \cdot t_{net}^j + t_{trav}$	$t_{tot}$
Pick-by-light	-	-	$2 \cdot t_{net}^j + t_{trav}$	$t_{tot}$
RFID pick-by-light	-	$2 \cdot t_{net}^j$	-	$t_{tot}$

The dependent time has been measured for the five picking systems presented above and the probabilities of occurrence of the errors have been estimated in Battini et al. (2015). To include the pick-by-vision system in the comparison study, one must first estimate the same parameters to be able to use the hourly cost function to assess its profitability.



# Chapter 5

## Testing the pick-by-vision solution

This chapter gives to the reader an insight of how the experiments has been conducted in the Logistics 4.0 laboratory with the in-house developed pick-by-vision system. As a reminder, the main objective of this testing phase is to measure the performance of the pick-by-vision solution in terms of picking time and errors, to be used as inputs for the economic model. Therefore, this chapter brings the main answers to the research question 2.

### 5.1 Description of the experiment

#### 5.1.1 Setup of the pilot warehouse

In the logistics 4.0 laboratory, a pilot warehouse has been established to simulate order picking in an industrial setting. The layout, as well as the configuration of the shelves, have been designed to replicate as realistically as possible a real warehouse with the help of the supervisor, who is experienced with working in warehouse environments.

The pilot warehouse consists of four shelves, with three or four racks each, totalling a number of 470 available stock locations. The products are stored in boxes and bins of different sizes and each stock location is assigned to a unique barcode, which is then assigned to the items stored in that particular box or bin. **Figure 5.1** shows the layout of the pilot warehouse at the logistics 4.0 laboratory.

#### 5.1.2 Proceeding of the experiment

This phase of the present study followed a similar empirical approach as Hanson et al. (2017), as mentioned in the methodology **Section 1.2**. Their research involve 5 persons



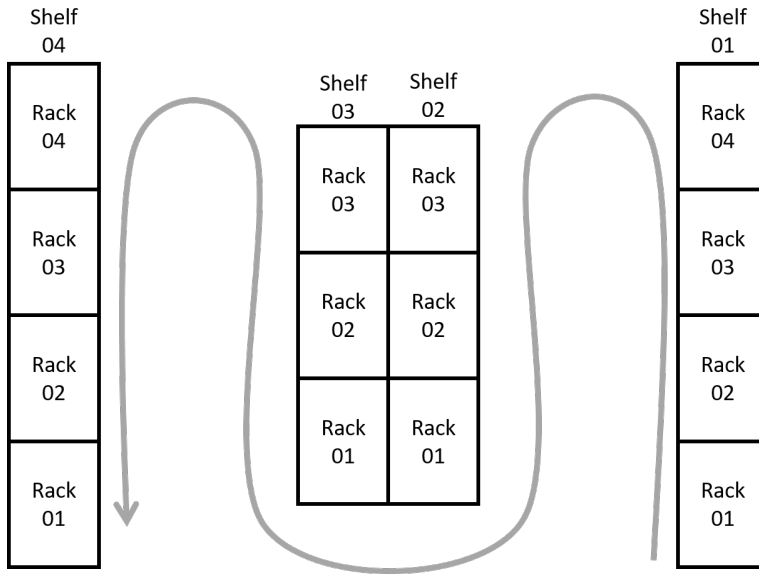
**Figure 5.1:** Layout of the logistics 4.0 laboratory pilot warehouse

have been tested for 10 picking lists consisting of 15 order lines each to evaluate the performance (picking time and errors) of their Hololens solution for kit preparation.

Arbitrarily, 10 test persons, 6 men and 4 women, aged from 20 to 40, have been chosen to take part in the experiment. Most of them are NTNU students without previous working experience in a warehouse and the supervisor was also included in the tests. For the experiment, 57 out of 470 stock locations have been filled with items along with their barcodes. These 57 products are then used to generate 7 different picking lists from which each picker has to pick 5. Each picking list consisted of 15 picking rows, with picking quantity varying from 1 to 3 items per order line.

Studies in the past have reported the existence of learning effects and fascination effects when using new technologies to perform order picking (Schwerdtfeger et al., 2011; Hanson et al., 2017). During the first use, test persons tend to spend time understanding the system or testing the system's capabilities and this could be translated in high variability in picking times and errors. To compensate for these effects, it is recommended to go through a training phase (also called try-and-ask phase) with the test persons before proceeding to measures (Schwerdtfeger et al., 2011; Hanson et al., 2017). Hence, it has been decided that each test person goes through a complete picking tour with 15 picking rows where they could ask any questions about the pick-by-vision system before measuring picking times and errors.

A timer is integrated in the Hololens application and starts when the picker says the keyword "run", which also triggers the blackboard to display information related to the first pick. The same timer stops after the picker has achieved the last pick of a given picking list. The floating blackboard in the glasses then displays the total time used to accomplish the picking list, as well as the number of wrong scans detected during that picking tour. The number of wrong scans corresponds directly to the number of errors type  $e_2$  (see **Section 2.2.4**). At the end of a picking tour, the picked items are put to where they belong, which allows the disclosure of any type  $e_3$  or  $e_4$  errors that have occurred during the



**Figure 5.2:** Common picking route for all the picking tours during the experiment.

picking tour.

It has also been noticed that the barcode scanning feature is not functioning perfectly at all times: the glasses sometimes detect wrong scan even though the right product was picked. A re-scan was then necessary to continue the picking tour. Consequently, these "fault-negative scans" should not be considered as errors type  $e_2$ . The number of these has been also recorded to be further discussed.

In total, 750 picking rows have been picked to estimate the picking time per row  $t_{tot}$ . The primary objective of these tests is to estimate the net picking time, which is the time component that is dependent on the considered picking system. Hence,  $t_{trav}$  also needs to be estimated, to be subtracted from the estimated  $t_{tot}$  to obtain  $t_{net}$ . Since the impact of the routing policy is not of interest of this paper, all the picking tours included the same S-shaped route, illustrated in **Figure 5.2**.  $t_{trav}$  has then been estimated by simply walking in the warehouse following the common picking route without performing order picking. An average of  $t_{trav}$  has been calculated from the time measured for 10 walks.

## 5.2 Results from the experiment

All the measurements of the different parameters can be found in **Appendix B**. The main results are summarized in this section. The average travelling time of a picking tour is estimated to be 46.102s (with a standard deviation of 6.688s). The average total time for a picking tour amounts to 190.662s (with a standard deviation of 23.282s). Therefore, the net picking time per picking tour is estimated to be 144.560s which gives a net picking

time (per row)  $t_{net}$  of 9.637s. The fastest and the slowest pickers have been recorded with  $t_{net}$  equal to 7.809s and 10.754s respectively.

Besides, the recorded errors are rather few. Only 5 type  $e_2$  errors, 1 type  $e_3$  error and 1 type  $e_4$  error occurred for all the test persons, resulting in error percentages of 0.67%, 0.13% and 0.13% respectively. However, a larger number of fault-negative scans have been recorded: 26 fault-negative scans for 750 items scanned, leading to a 3.47% dysfunction rate of from the barcode feature.

These results will be used in the economic model in the next Chapter.

### 5.2.1 Feedback from test people

All of the test persons reported that they identify the pick-by-vision solution as an efficient system, that they believe that using smart glasses for order picking leads indeed to a gain in productivity (compared to the traditional pick-by-paper for example). They felt comfortable with the floating blackboard and found the grid-based visualization very intuitive. Besides, they think that scanning barcodes with the glasses is rather useful for such operations, even though it did not feel very natural for some of them at the beginning.

Nonetheless, several test persons stated that wearing the HoloLens is not very comfortable, primarily due to its weight. Furthermore, despite of the design efforts to make the visualization comfortable for the user, a minority of test persons reported to feel a little nauseous and/or tired at the eyes' level towards the end of the experiment (approximately 1 hour for each person).

Required quantity is not disclosed to the picker when the location is first shown. The operator has to wait until the scan is correct for the pick quantity to be revealed. As a result, when more than one item has to be picked, the operator has to perform the physical pick at least twice, in addition to reading the instructions on the blackboard twice. This has been reported to be a little tedious, time consuming and a little frustrating for some pickers.

It has also been stated that showing the shelf and rack numbers was not always enough to incite the picker to move from the shelf he/she was facing. After a successful pick, the test persons tended to look at the blinking green box before reading the text about the shelf and the rack. As a result, they sometimes searched the product in the shelf they were facing at the previous pick before realizing that they were standing in front of the wrong shelf.

Schwerdtfeger et al. (2011) reported some weaknesses in their tunnel-based visualization when the picker stood too close to the shelf. This problem has not been witnessed during the trials of the present solution. It has been noticed that the blackboard tend to disappear when the user's head gets too close to the shelf, but this is not a common behaviour. This usually happens when the user has to stretch out to grab an item on the highest or the lowest level on the shelf, in which case he/she already knew the location of the product and did not need the information on the blackboard at that particular moment.

# Chapter 6

## The comparative analysis using the economic model

In this chapter, results from the experiment described in **Chapter 5** will be integrated in the economic model introduced in **Chapter 4**. In other words, this chapter aims to evaluate the pick-by-vision solution with the Hololens in terms of performance and costs, in comparison with other order picking solutions.

### 6.1 Important assumptions

In Battini et al. (2015), the economic model has been applied for each of the presented technologies for two warehouses with two layouts and two different number of available stock locations,  $n_{SL} = 2000$  (referred as warehouse A) and  $n_{SL} = 50$  (referred as warehouse B). It is important to be aware that the picking time of each picking system might be affected by the layout of a given warehouse, in terms of travel time and net picking time. The authors reported that travel time was significantly shorter in the warehouse B that was equal to 20 seconds, as opposed to 120 seconds in warehouse A. Likewise, due to a single shelving configuration, operators have been observed to be spending slightly less time searching for an item, as well as picking and storing it in the cart in warehouse B than in warehouse A. Nonetheless, no difference has been stated in regard to errors' probabilities and the corresponding time factors.

To be able to make a relevant comparison from the results at the logistics 4.0 laboratory, some assumptions have to be made. According to the supervisor of the present paper, the pilot warehouse in the logistics 4.0 laboratory resembles a lot to warehouse A in terms of layout, density of products, the way the products are stored etc. Therefore, an important assumption is that the travelling time is the only parameter which is different from the warehouse A and the pilot warehouse in the logistics 4.0 laboratory. With a similar config-

uration, we assume that the net picking time is the same for both warehouse A and the pilot warehouse, for each of the studied picking systems. In this way, it is possible to assess the profitability of the pick-by-vision solution as if it has been tested in the warehouse A.

In regard to picking errors, it has been observed that the tests in the logistics 4.0 laboratory could not lead to realistic conclusions because there were not enough products in the stock locations, which significantly reduces the chances of the operator picking wrong items. If a test person wanted to pick from an empty box, he/she immediately knew that the pick was wrong and corrected the pick at the same time (instead of realizing it at the end of the picking tour). As a result, another assumption was that the error occurrence probabilities would be the same for pick-by-vision and for the barcode handheld, as barcode scanning is one of the features of the current Hololens application. Besides, the times factors corresponding to each error will be the same ( $t_{tot}$  and  $t_{net}$  taking different values of course). As a reminder, there is no error  $e_1$  for the considered pick-by-vision system (see **Section 3.3**).

In conclusions, the approach has then been the following: first, the net picking time has been measured experimentally to be used as an input for the economic model, then the pick-by-vision system is included in the Battini et al. (2015)'s comparative analysis by simulating the use of the hololens solution in warehouse A with the consideration of  $t_{trav} = 120$  seconds and assuming that the error probabilities are the same for the barcode handheld and the pick-by-vision system.

## 6.2 Application of the economic model

In this section, the hourly cost function is used to assess the viability of the considered picking system. Undoubtedly, the investment in a pair of Hololens represents a considerable cost for a given company (the price of the hardware is \$3000). This section aims to shed the light on whether the gain in productivity with a pick-by-vision system is worth the investment or not, which is also the main contribution of the present thesis. First, some note-worthy explanations for several parameters in the economic model is given here.

The fixed costs  $c_F^j$  corresponding to the software and the server costs will be considered being the same for all the picking systems (30000€). Likewise, the work of one picker costs about 30€ per hour for all the considered technologies. According to the supervisor, a picking cart of the value of 1000€ is also included in the picker device cost  $c_{d,P}^j$  for each for the picking systems. A time period of two years with an eight-hour work shift per day and 220 working days per year, totaling 3520 hours, is considered as a reference to amortize the stock location costs, the picker device costs and the fixed costs. Since the current pick-by-vision solution includes barcode scanning, the stock location unitary cost will be the same as the barcode handheld picking system ( $c_{SL}^j = 1.10€$ ).

The values of the different parameters for each picking system can be found in **Appendix A**. The different picking systems are being compared for different numbers of requested picking rows per hour  $n_R$ . This will allow the warehouse manager to know which solution is the most profitable depending on the demand from the customer orders

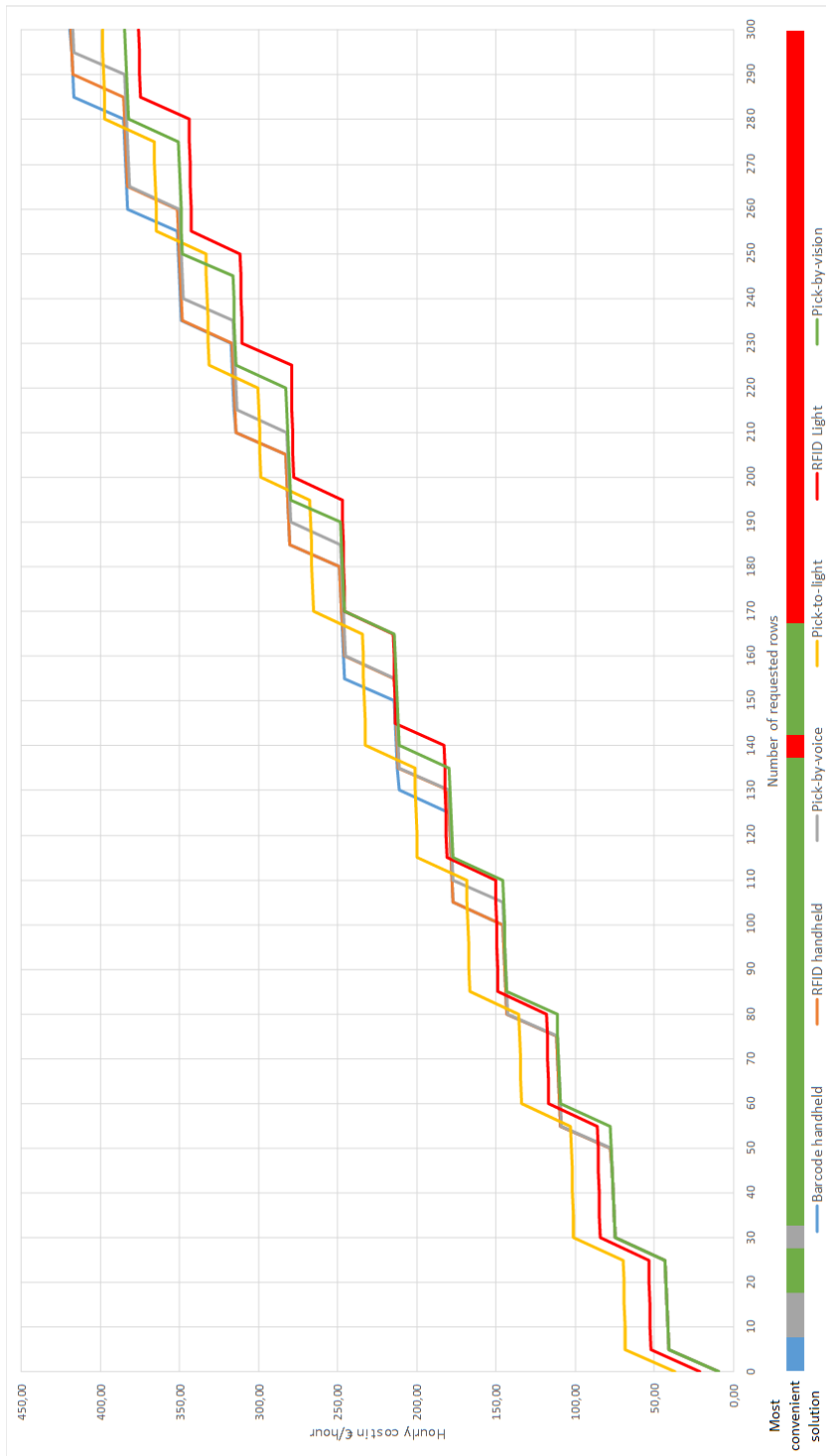


Figure 6.1: Hourly cost function for the different picking systems.

(translated in picking rows).

**Figure 6.1** gives a visualization of the results. A rather obvious observation is that the hourly cost function increases with  $n_R$ , mainly because the company needs to hire more pickers to keep up with the demand from the customers' side, regardless the employed picking system (Battini et al., 2015). In terms of picking performance, the pick-by-vision system with an estimated net picking time of 9.64s is a more efficient picking system than the barcode handheld, the RFID handheld and the pick-by-voice system whose net picking times are 19.83s, 18.29s and 15.94s respectively. This means that a picker equipped with the HoloLens can reach higher picking rates than with the three other mentioned technologies. The reason behind such a picking speed may originate from the ability of showing a rather intuitive visualization of the items' location, leading to shorter search times. The operator is also assisted with a hand-free device, contrary to the barcode handheld or the RFID handheld systems, resulting in shorter physical pick and confirmation times. Since the information is directly projected at eye level, the operator does not need to make back and forth head movements to look at a screen or paper or to wait for the instructions given by voice, which also reduce the getting information time. Although associated with a quite close net picking time, it does not outperform the pick-by-light and the RFID pick-by-light systems, with net picking times equal to 8.69s and 7.71 respectively.

In regard to profitability, **Figure 6.1** also shows the preferred technology (with the lowest hourly cost) depending on the requested picking rate. One can see that for  $n_R \geq 170$  rows/hour, the RFID pick-by-light is still the dominant technology, in accordance with the findings from Battini et al. (2015). This can be explained by its short net picking time, along with low error probabilities. However, for most of the lower  $n_R$ s, the HoloLens solution turns out to be the most convenient picking system. The investment for a pick-by-HoloLens system leads to a picker devices cost  $c_{d,P}^j$  about 1000€ higher than the five other picking systems: 3700€ for the HoloLens solution against 2800€ for barcode handheld, 2900€ for RFID handheld, 3000€ for voice-picking, 2800€ for pick-by-light and 2600€ for RFID pick-by-light. But it can result in satisfactory picking rates as explained earlier while having the costs associated stock location quite low (same as the barcode handheld system, 1.10€ per stock location), contrary to the traditional pick-by-light and the RFID pick-by-light systems, whose  $c_{SL}^j$  amounts to 50€/unit and 22.30€/unit respectively.

What is also interesting to analyze in **Figure 6.1** is the potential gain from switching from one picking system to another. As explained earlier, the curves are following the same trend when  $n_R$  is increasing. But for a given  $n_R$ , the differences between the hourly cost functions of two picking systems might either be very small or rather significant. For instance, at  $n_R = 170$  rows/h, adopting either of the picking systems (except the traditional pick-to-light system) will not change the hourly cost much. However, at  $n_R = 270$  rows/h, opting for the RFID pick-by-light system will allow the company to save up to 40€/h, as opposed to opting for a pick-by-voice system for example.

On another note, the HoloLens hardware costs \$3000 (the developer package), but companies may opt for the commercial suite whose price is up to \$5000 to benefit from enterprise features for added security, device management and a warranty (Microsoft, 2019a). In the case where the company wants to acquire these services, the economic assessment needs to be adjusted. Once purchased for the first device, the commercial suite features



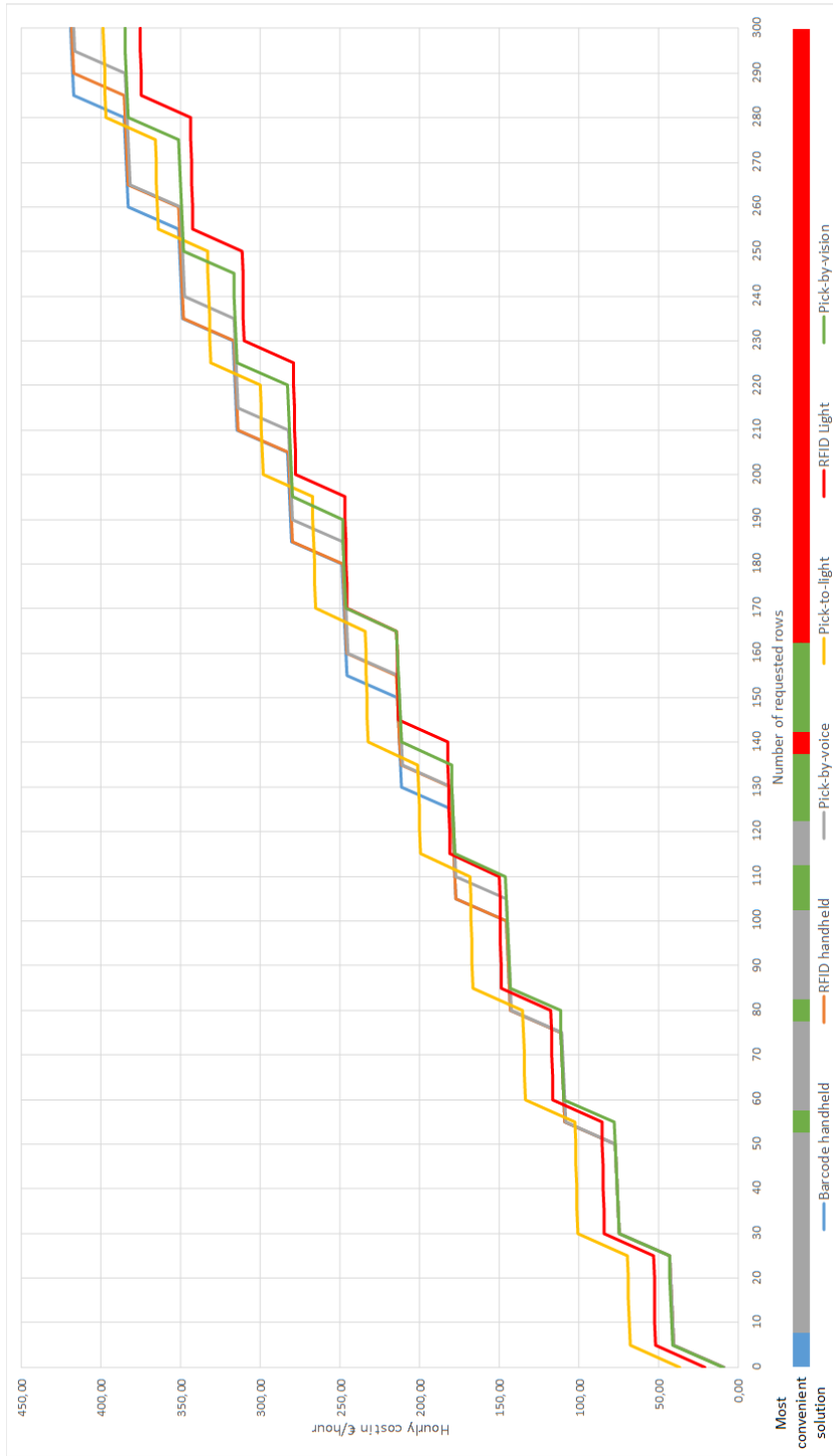


Figure 6.2: Hourly cost function for the different picking systems with the Hololens commercial suite case.

will be available for the other Hololens devices from the same company. In the model, the fixed costs for the Hololens solution are then updated to 31800€(the 1800€corresponding to the difference of \$2000 in the price between the commercial suite and the classic developer package).

One can see that RFID pick-by-light is still the most convenient solution for  $n_{RS} \geq 170$  rows/h, which was an expected outcome. However, for the more than half of the  $n_{RS} \leq 160$  rows/h, voice-picking outperforms the Hololens solution, which means that the extra investment is no longer compensated by the gain in productivity. However, by looking at the graph closely, the difference between both curves is in fact barely noticeable when voice-picking is preferred over pick-by-vision. Consequently, if a given company is hesitant when it comes to investing in the commercial suite of the Hololens, **Figure 6.2** shows that the pick-by-vision solution is still a very viable candidate for  $n_{RS} \leq 160$  rows/h.

## 6.3 Sensitivity analysis

A sensitivity analysis is defined as "the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input" (Saltelli et al., 2004). The hourly cost function has been calculated using the values of the net picking time and the error probabilities, which have been assumed or estimated from the laboratory tests for the considered pick-by-vision system. This means that the values of these two parameters cannot be known with certainty. More generally speaking, it is difficult to define an exact value for the picking time and the error probabilities, as the picking performance varies from one picker to another, regardless the employed picking system. The results from the experiment presented in **Section 5.2** has indeed shown a significant standard deviation in the measurements. A sensitivity analysis is then conducted here to analyze how the outcome (the most convenient picking system depending on  $n_R$ ) can be impacted with some variations in the values of the two mentioned parameters. For this purpose, the investment in the commercial suite of the Hololens is not considered ( $c_F^j = 30000\text{€}$ ). The variations of the parameters have also been considered individually (only one parameter was varying at a time).

### 6.3.1 Variation of the net picking time

From the results presented in **Section 5.2**, the fastest picker from the test persons recorded an average net picking time of 7.80s against 10.75s for the slowest picker. This gives a good indication about the range of the actual net picking time of the studied pick-by-vision system. It has thus been decided to consider variations of net picking time from 7.5s to 11s to analyze the potential outcome, i.e. the most convenient picking system depending on  $n_R$ . **Figure 6.3** gives a visualization of the results.

One can notice that the results do not vary much with the variation of the net picking time of the pick-by-vision system, at least in the [7.5;11] seconds range (the results from



Figure 6.3: Sensitivity analysis with variations of the net picking time of the pick-by-vision system.

the previous section are presented in **Figure 6.3** and are highlighted with a yellow frame). One can still observe the trend of voice-picking becoming the most convenient system (replacing the pick-by-vision system) for the low  $n_{RS}$  when the net picking time of the pick-by-vision system is raising.

### 6.3.2 Variation of the picking error probabilities

The approach has been the same here, but the variation range is chosen arbitrarily this time. However, since there are three types of potential errors for the Hololens solution (no  $e_1$ ), three sensitivity analyses addressing each of the three types of errors have been conducted separately. The results of the three analyses for  $e_2$ ,  $e_3$  and  $e_4$  are shown in **Figure 6.4**, **Figure 6.5** and **Figure 6.6** respectively.

Sensitivity analysis with variations for  $e_2$  leads to roughly the same conclusions as the previous section, which translates in no significant changes in the results when probability of occurrence of  $e_2$  is varying. This may be explained by the short time required to bring the necessary corrections to an error type  $e_2$ , which equals to  $2 \cdot t_{net}^j$  (see **Table 4.2**).

Nevertheless, changes in the outcome are more obvious when the variations concern  $e_3$  and  $e_4$ . **Figure 6.5** and **Figure 6.6** are rather similar and the same conclusions can be drawn from both. On one hand, for the probabilities that are higher than the initial probabilities, meaning that  $e_3$  and  $e_4$  have more chances to occur, pick-by-vision becomes less preferred than the pick-by-voice for low  $n_{RS}$  (with no changes for the high  $n_{RS}$ ). On the other hand, when the probabilities are set lower than the initial values, pick-by-vision progressively becomes the most convenient picking system for the higher  $n_{RS}$ , replacing the RFID pick-by-light system. The reason behind such an observation is that since  $e_3$  and  $e_4$  are only detectable at the end of the picking tour, they require more time to the picker to bring the necessary correction actions (see **Section 2.1** and **Section 4.2**) and are therefore more costly to the company.

Intuitively, the lower the error probabilities are (especially in regard to the propagating errors which are costly to fix), the more profitable a picking system is, which explains the popularity of the RFID pick-by-light in the first place. The sensitivity analyses have subsequently shown that the economic model is more sensitive to changes in error probabilities, specifically the ones concerning  $e_3$  and  $e_4$ , than in net picking time.

## 6.4 Qualitative comparison of the different picking systems

Until now, the comparison has mostly been quantitative using the economic model. Even though it is not the primary objective of the present study, this section aims to provide a qualitative perspective to the comparison, since each of the picking systems presents some advantages and disadvantages which cannot always be evaluated in a quantitative way. The focus is still centered on the pick-by-vision system.



Figure 6.4: Sensitivity analysis with variations of the  $e_2$  probability of occurrence of the pick-by-vision system.

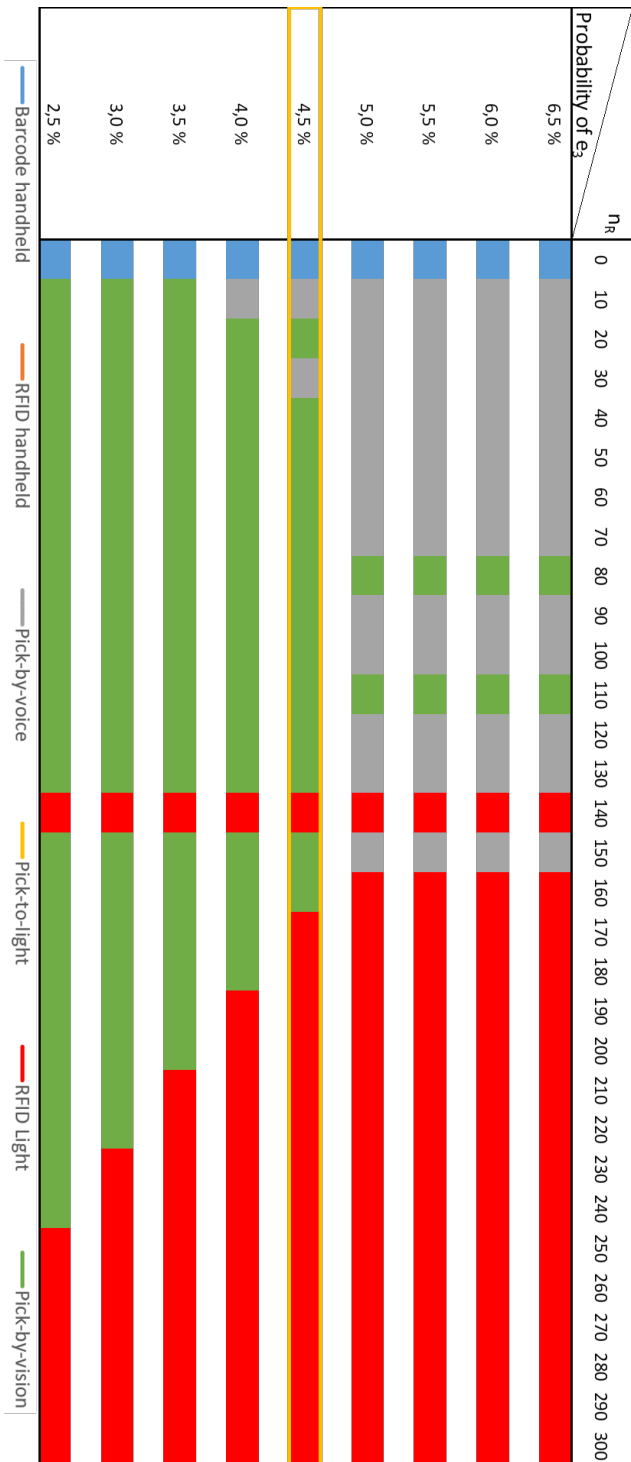


Figure 6.5: Sensitivity analysis with variations of the  $e_3$  probability of occurrence of the pick-by-vision system.

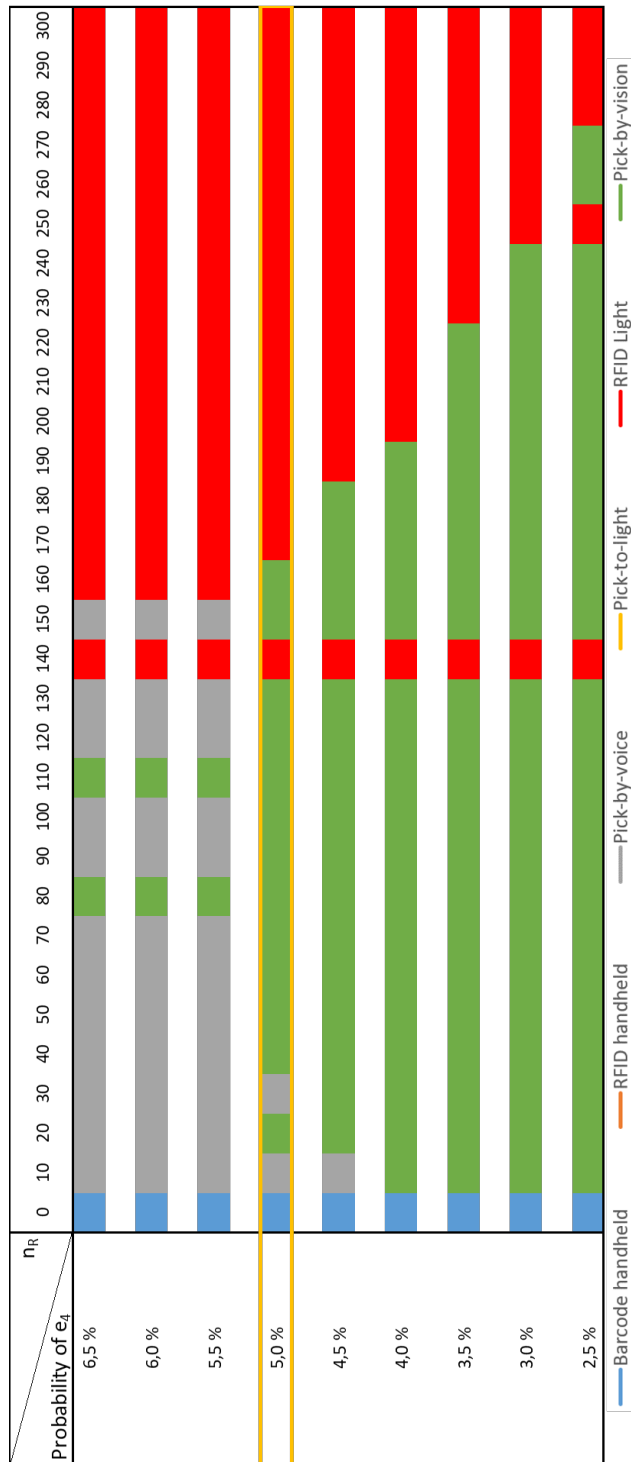


Figure 6.6: Sensitivity analysis with variations of the  $e_4$  probability of occurrence of the pick-by-vision system.

### 6.4.1 Advantages of the pick-by-vision solution

First of all, all the considered picking systems share the same ecology argument: by adopting one of these picking systems, the traditional pick-by-paper system is then avoided at the same as the extensive use of paper.

As mentioned in **Section 2.3**, order picking is not the only potential use of smart glasses in an industrial environment. They can be adopted for other applications such as assembly, maintenance, quality control or material handling. If used for several purposes, the costs of investing in a pair of HoloLens can be amortized significantly. However, one must keep in mind that in the economic model, the pair of HoloLens was considered being used continuously for order picking in the daily 8 hours shift.

Accordingly to what has been mentioned above, having the barcode scanning feature directly integrated inside the HoloLens allows the user to benefit from the item confirmation phase without require the use of one hand, as opposed to the barcode handheld or the RFID handheld systems, making the picking operations smoother.

The pick-by-vision system is also a rather intuitive system which does not require extensive training to learn how to use. Each of the test persons confirmed that he/she became quite familiar with the system after performing the picks on the test picking list. One of the main advantages of the pick-by-vision system is that the smart glasses are able to project information or instructions directly at eye-level. Thus, the operator can understand quickly the steps he/she is supposed to follow during the process, without demanding much focus effort (Stoltz et al., 2017).

For instance, a voice-picking system may require great focus efforts from its user as he/she has to listen carefully to the given instructions and interpret them. The focus issue is to some degree less obvious with the pick-by-vision solution, as the information is displayed at eye level. From the supervisor's past work experiences with warehouses, another issue that pick-by-voice system may face some is when the company is employing some foreign workers. Due to the language barrier, vocal interactions may not be as smooth as it should be, specifically during the confirmation phase, where the picker has to read the last digits of the barcode of a given SKU. In the current pick-by-vision system, vocal inputs are only required at the very beginning of the picking tour (to select the picking list and to start the timer). This has been part of the author's design choices, but vocal commands can be totally avoided in a pick-by-vision system if desired.

Besides, pick-by-light and RFID pick-by-light systems rely on a significant investment and some manual effort to install the light systems on the shelves at the very beginning before the operator can start working. As precisely each stock location is allocated with one light system, changing the shelves' configuration becomes very difficult once the light systems are attached to the racks, leading to a very inflexible system. If the company decides to add more stock locations with the use of smaller boxes or bins for example, existing light systems need to be removed from the racks, new light systems need to be purchased and installed on the racks again (perhaps along with some of the existing light systems which can be reused). With a pick-by-vision system, physical changes are not required, but the visualization needs to be adapted. In the current pick-by-vision system,



grids illustrating the racks needs to be modified digitally and the size and the position of the green blinking box needs to be adjusted. In practice, such adaptation efforts are less tedious.

### 6.4.2 Drawbacks of the pick-by-vision solution

The battery of the Hololens only lasts for 2-3 hours (Microsoft, 2019b), which do not cover a full eight hours shift a day. A long lasting battery is however identified as one of the key element for a successful AR solution in Stoltz et al. (2017). A viable option could be to keep a portable charger in the pocket and to plug it to the hololens during use, but it represents additional investments.

Accordingly to what has been presented in **Section 5.2.1**, the hardware weighs up to 579g (Microsoft, 2019b), which is the primary cause of the reported discomfort from several test persons. The latter have stated that they experience soreness for different areas around the head and/or the neck. Besides, even though it has only concerned a minority of people during the tests, the Hololens seems to be potentially tiresome for the eyes. Such conditions may become unbearable in a real-life industrial scenario, where the headset is worn for the continuous extensive time interval of 8 hours.

Some test persons wearing prescription glasses have experienced some difficulties wearing the Hololens as the prescription glasses need to fit underneath the headset, but they felt comfortable afterwards as the the experience only lasted for about an hour. Longer periods of use need to be tested to determine whether the Hololens can cause strain on the nose or or the back of the ears because of the glasses frame or again additional tiredness for the eyes for people wearing prescription glasses.

The integration of barcode scanning has proven to be functional in the present study, but the findings from Stoltz et al. (2017) about the smart glasses being not as reliable as commercial scanners or smartphone cameras in terms of barcode scanning performance are also valid. Some trials done during the present study have proven that barcode shapes and sizes do have an impact on scanning results with the Hololens. The current application is able to scan a rather large barcode (roughly 3cm x 9cm) that is stuck to a flat surface (typically plates from the experiment) from a distance about 40-50 centimetres. Smaller barcodes (than half of the indicated size) or barcodes that are stuck on a bent or rounded surface (balls or cups for example) are not detected at all by the Hololens.

As mentioned in **Section 5.2**, about 3.47% of the scans have been detected as wrong while the right items were picked, which makes the barcode scanning feature with the Hololens questionable. In addition to causes related to the hardware's capabilities, a fault-negative scan may originate from the picker scanning the item from an inappropriate reading distance (too far or too close) or angle (barcode not perfectly facing the glasses) and/or from the picker hiding parts of the barcode with his/her finger. Another potential scenario for fault-negative scans is when the picker clicks to proceed to the next pick while still having the previous item in front of his/her eyes: the same barcode is then read twice, resulting in a successful scan for the first time and a wrong scan for the second time.

Besides, as mentioned in **Section 1.2**, investing in the hardware is not enough as there

is no generic pick-by-vision application for the Hololens. If a given company does not want to involve a third-party logistics solution provider (not to generate further expenses for example), they need to develop their own application to be run on the hardware they purchased, which requires computer programming skills.

## 6.5 Summary of the findings and further discussion

The economic model from Battini et al. (2015) has been used to assess the performance of the developed pick-by-vision system from both the productivity and the economic perspectives. Including the economic aspect in the evaluation of the pick-by-vision system is the main originality of the present paper, in comparison with other studies on the same topic from the literature. To be able to use the economic model, the picking productivity with a pick-by-vision system developed specifically for this study has first been estimated thanks to a testing phase in a laboratory setting. The considered pick-by-vision system is then included in a comparative analysis with five other picking systems. The findings from this study can be beneficial to warehouse managers in decision support regarding future investments in order picking systems. A summary of the pro and con arguments for investing in the considered pick-by-vision system is suggested in **Table 6.1**.

**Table 6.1:** Summary of the pros and cons for investing in the considered pick-by-vision system

Pros	Cons
Quantitative arguments	
Most convenient picking system for most of the $n_R < 170$	Outperformed by RFID pick-by-light for $n_R \geq 170$
Satisfactory net picking time $t_{net} = 9.67s$	High investment: \$3000 hardware or \$5000 commercial suite
Qualitative arguments	
Ecology argument: use of paper significantly reduced	Short-lasting battery: about 2-3 hours of use with one charge
Multiple potential applications in other operations	Potential head and neck soreness due to the hardware's weight
Hand-free device	Potential tiredness at eye level due to the visualizations
Intuitive system: does not require extensive training or focus	Potential discomfort with people wearing prescription glasses
Flexible to warehouse configuration changes	Limited barcode scanning performances
	Requires computer programming

The reader must bear in mind the economic model has been applied in the warehouse A configuration only, where the travelling time is  $t_{trav} = 120s$ . As a reminder,  $t_{trav}$  strongly influences the total picking time and is independent from the considered picking system. If the picker always has to travel a lot between two picks, the impact of the employed technology is less noticeable Battini et al. (2015) and vice versa. The warehouse layout, the configuration of the stock locations as well as the product characteristics (size, weight etc.) also play a major role in influencing the picking performance of a given picking

system. Hence, the economic assessment varies significantly from a warehouse to another, which is empirically shown in Battini et al. (2015).

The present assessment is also limited to the pick-by-vision system specifically developed for this study. As mentioned in **Section 3.1**, there are many ways to design a pick-by-vision system, which strongly affect the efficiency of it. Therefore, the findings of this study cannot be generalized to all the pick-by-vision systems.

Likewise, the present pick-by-vision system is specifically designed for the Hololens, but the market offers multiples choices of smartglasses with a large range of capabilities and prices. The warehouse managers may opt for another model of smartglasses with various advantages and drawbacks (the reader is referred to Syberfeldt et al. (2017) which addresses precisely this topic), but the pick-by-vision system may be designed differently according to the chosen model. This will undoubtedly lead to different results from the economic model.

According to Syberfeldt et al. (2017), one can expect the prices of smart glasses to decrease in the coming years, as they are becoming more and more broadly adopted by companies. As a result, the economic assessment conducted in this paper is also expected to change and pick-by-vision may become a more an more profitable picking system in the future.

Finally, the sensitivity analyses only considered the net picking time and the probabilities of occurrence of errors of the pick-by-vision system, and their variations has been treated separately. Considering the variation of more than one parameter at a time can be time-consuming, but offers a better insight of how the outputs are affected by the inputs. The parameters from other picking systems remained constant, and considering their variations would also be relevant since these values cannot be known with certainty as well. Understanding how the other parameters such as travel time, or picker hourly and so on, influence the outcome could be beneficial to warehouse managers as well since they can take the decisions to modify these values (tactical decisions such as changing the layout or by outsourcing the workforce for example).



# Conclusion

This paper aimed to evaluate the potential of using smart glasses for order picking operations. For this purpose, a pick-by-vision system with the HoloLens has been developed specifically for this study. The developed system has then been tried with 10 test people in a pilot warehouse established in the Logistics 4.0 laboratory in order to estimate its picking performance in terms of picking time and picking errors. With some assumptions, the results from the experiment allowed the use of Battini et al. (2015)'s economic model to conduct a comparative analysis with 5 other picking systems. The comparative analysis aims to support decision-making for warehouse managers in regard to the investment in a new order picking system, as the economic perspective is included in the study, which is the main originality of the present research.

## 7.1 Research questions and objectives

As a reminder from the introduction chapter, the main objective was "to assess the pick-by-vision system, from both productivity and economic perspective and to compare it with other order picking systems", with a sub-objective of "developing an efficient in-house pick-by-vision system that will be tested in the laboratory". To achieve these objectives, three research questions were set to guide the research of this thesis. Here are presented the findings to each research question:

### 1. **What features should a pick-by-vision system include to best support an operator in order picking operations?**

It is crucial to understand the strong link between the picking performance and the design of the picking system, which is the purpose of the **Chapter 3**. From the literature study, the main focus when developing a pick-by-vision application should

be on designing a comfortable, intuitive and non-obstructive visualization. After some trials, the final visualization consists of a floating blackboard displaying the shelf and rack numbers in text and a grid replicating a rack, along with a blinking green box showing the to-be-picked location. Although it was not meant to be a main contribution, the present study showed the possibility of including the barcode scanning feature in a pick-by-vision system to benefit from the confirmation phase during the picking process. Colour coding and sound effects were also added to facilitate the understanding of the displayed information by the user. The results have proven to be satisfactory, according to the received feedback in **Section 5.2.1**.

**2. What are the gains in terms of productivity by adopting a pick-by-vision system?**

This research question is mainly answered in **Chapter 5**. In order to determine an average total picking time per picking tour, 10 persons took part in the tests, performing order picking with the Hololens application in the pilot warehouse in the laboratory. Then, the total net picking time is obtained by subtracting the travel time from the total picking time and the result gives the average net picking time of  $t_{net} = 9.637s$ , which is very promising compared to the net picking time of other picking systems. Besides, very few picking errors have arisen during the tests, but it enabled to shed the light on the potential dysfunction of the barcode scanning feature thanks to the recorded number of fault-negative scans.

**3. In comparison to other picking systems, how profitable is the investment in a pick-by-vision system? What are the potential advantages and drawbacks?**

In **Chapter 6**, the hourly cost functions of the 6 considered picking systems are calculated for different number of requested picking rows per hour  $n_R$  to determine which picking system is most profitable according to the demand from customer orders. The Hololens solution revealed to be the preferred picking system for most of the  $n_{RS} < 170$  rows/hour, but was outperformed by RFID pick-by-light for higher  $n_{RS}$ . Moreover, from a qualitative perspective, the considered pick-by-vision offers some advantages such as being an eco-friendly, intuitive and flexible system and employing a hand-free device which is applicable in other industrial activities. On the other hand, the drawbacks of the Hololens solution are the short-lasting battery, the potential caused discomfort, the limited barcode scanning performance and the need for computer programming to develop the software. The main findings are summarized in **Table 6.1**.

## 7.2 Limitations

This section addresses the limitations of the present study, which is in keeping with has already been discussed in **Section 6.5**, but the discussion here is more oriented towards the potential sources of error of the present study.

First of all, the experiment was conducted in a laboratory setting, which means that the measured picking performance might deviate from the actual picking performance in a real warehouse. As there were only four shelves, the picker never had to travel for more than a few metres between two picks, making the estimation of the travelling time very difficult. It can be argued that the employed method in this paper only gives a rough estimation of  $t_{trav}$ , calling therefore the validity of the estimation of  $t_{net}$  into question.

The test persons only had one picking list during the training phase. In a more realistic scenario, operators usually tend to get faster and faster after a certain amount of practice, which means the picking performance of the HoloLens might be higher in practice. On the other hand, as the picker were only tested for a short period of time, effects related to tiredness, loss of focus etc. could not be observed and analyzed with consistency.

Only 57 out of 470 boxes are actually filled with products and the picking quantity did not exceed 3 per order line because printing out the necessary barcodes, sticking them on the corresponding products and putting the right products at the right locations was very laborious and time-consuming. As a consequence, measurements regarding the picking errors could lead to consistent conclusions, which led the economic assessment to rely on some strong assumptions (same error probabilities as the barcode handheld system). The appropriateness of the latter could be questionable, as the occurrence of picking errors may actually be reduced thanks to the featured intuitive visualization for example. Moreover, the sensitivity analyses have revealed the hourly cost function to be rather sensitive to error probabilities variations.

As a consequence, results from the comparative study have to be looked with a fresh pair of eyes. The present paper's aim was to provide a first general economic evaluation of the pick-by-vision solution to get the big picture.

## 7.3 Further work

To overcome the mentioned limitations, further work could be focused on a more rigorous experimental approach to measure the picking performance of the present pick-by-vision system. After filling up all the boxes with items, the methodology from Battini et al. (2015) with video recordings and so on, can be used to determine each individual component of the net picking time  $t_{net}$  and the error probabilities, enabling a comparative analysis with more consistent results and less assumptions. Ideally, the pick-by-vision should be tested in a real industrial setting.

The Logistics 4.0 laboratory will acquire the pick-by-vision system from LUCA Logistic Solutions (2016) in the near future. Since the designed visualization is different, the resulting picking performance may also differ from picking with the HoloLens application from this study. It could then be included in the same comparative study to offer insight of a new alternative to warehouse managers. Such comparison will be even more relevant here, as both systems would be tested in the same setting. The economic evaluation can also be extended by taking different smart glasses models into account. In this case, the guidelines given by Syberfeldt et al. (2017) can be useful.

Further research could also be oriented towards the improvement of the existing pick-by-vision system. Modifications in the application can be brought following the feedback from the test people and the experimental approach for an optimal design could be inspired by Schwerdtfeger et al. (2011). Combination with the mentioned RFID-glove and tags or voice confirmation could also be possibilities for improvement.

Finally, from a discussion with some of the authors of Hanson et al. (2017), an interesting research direction could be to investigate the integration of such a pick-by-vision system with ERP (enterprise resource planning) or WMS (warehouse management system), as it would facilitate the adoption of the technology in the future.



# Bibliography

- Andriolo, A., Battini, D., Calzavara, M., Gamberi, M., Peretti, U., Persona, A., Pilati, F., Sgarbossa, F., 2013. New pick-to-light system configuration: a feasibility study. In: Proceedings of the XVIII Summer School F. Turco. pp. 1–10.
- Azuma, R. T., 1997. A survey of augmented reality. *Presence: Teleoperators and Virtual Environments* 6 (4), 355–385.  
URL <https://doi.org/10.1162/pres.1997.6.4.355>
- Battini, D., Calzavara, M., Persona, A., Sgarbossa, F., 2015. A comparative analysis of different paperless picking systems. *Industrial Management & Data Systems* 115 (3), 483–503.  
URL <https://doi.org/10.1108/IMDS-10-2014-0314>
- De Koster, R., Le-Duc, T., Roodbergen, K. J., 2007. Design and control of warehouse order picking: A literature review. *European Journal of Operational Research* 182 (2), 481 – 501.
- DHL, 2015. Vision picking at dhl - augmented reality in logistics. Accessed: 2019-03-09.  
URL <https://www.youtube.com/watch?v=I8vYrAUb0BQ>
- Goetschalkx, M., Ashayeri, J., 1989. Classification and design of order picking. *Logistics World* 2 (2), 99–106.  
URL <https://doi.org/10.1108/eb007469>
- Grosse, E. H., Glock, C. H., Jaber, M. Y., Neumann, W. P., 2015. Incorporating human factors in order picking planning models: framework and research opportunities. *International Journal of Production Research* 53 (3), 695–717.  
URL <https://doi.org/10.1080/00207543.2014.919424>
- Guo, A., Starner, T., Raghu, S., Xie, X., Ismail, S., Luo, X., Simoneau, J., Gilliland, S., Baumann, H., Southern, C., 09 2014. A comparison of order picking assisted by head-up display (hud), cart-mounted display (cmd), light, and paper pick list. In: Proceedings of the 2014 ACM International Symposium on Wearable Computers. pp. 71–78.

- 
- Hanson, R., Falkenström, W., Miettinen, M., 2017. Augmented reality as a means of conveying picking information in kit preparation for mixed-model assembly. *Computers Industrial Engineering* 113, 570 – 575.
- Itizzimo, 2013. Connect smart glasses and sap with the simplifier. Accessed: 2019-03-09.  
URL <https://www.youtube.com/watch?v=ZWsBHISOqjA>
- Joinpad, 2017. Smart logistics solution for hololens. Accessed: 2019-03-08.  
URL <https://www.youtube.com/watch?v=3UAgOmY8rLk>
- Kothari, C. R., 2004. *Research methodology : methods techniques*.
- Lambert, D. M., 1998. *Fundamentals of logistics management*. Irwin/McGraw-Hill, Boston.
- LUCA Logistic Solutions, 2016. Luca pick by vision hololens 1. Accessed: 2019-05-01.  
URL <https://www.youtube.com/watch?v=k58TlSCY69E>
- Microsoft, 2016. Microsoft hololens: The science within - making comfortable holograms. Accessed: 2019-04-10.  
URL [https://www.youtube.com/watch?v=-606oZKLa\\_s](https://www.youtube.com/watch?v=-606oZKLa_s)
- Microsoft, 2019a. Microsoft official website. <https://www.microsoft.com/>, accessed: 2019-05-01.
- Microsoft, 2019b. Mixed reality documentation. <https://docs.microsoft.com/en-us/windows/mixed-reality/>, accessed: 2019-03-15.
- Pan, Z., Cheok, A. D., Yang, H., Zhu, J., Shi, J., 2006. Virtual reality and mixed reality for virtual learning environments. *Computers Graphics* 30 (1), 20 – 28.  
URL <http://www.sciencedirect.com/science/article/pii/S0097849305002025>
- Picavi, 2015. Picavi: Vision picking with smart glasses. Accessed: 2019-03-08.  
URL <https://www.youtube.com/watch?v=B6zPnVGS0VI>
- Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. *Sensitivity analysis in practice: a guide to assessing scientific models*. John Wiley Sons, Ltd.
- Scandit, 2018. Augmented reality innovation in transport logistics with drone and hololens. Accessed: 2019-04-05.  
URL <https://www.youtube.com/watch?v=QkhX40oruuE>
- Schan, C., 2019. A pick by vision system with the hololens.  
URL [https://www.youtube.com/watch?v=rBW\\_Y8xUhE0](https://www.youtube.com/watch?v=rBW_Y8xUhE0)
- Schwerdtfeger, B., Reif, R., Günthner, W. A., Klinker, G., Jun 2011. Pick-by-vision: there is something to pick at the end of the augmented tunnel. *Virtual Reality* 15 (2), 213–223.  
URL <https://doi.org/10.1007/s10055-011-0187-9>

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Stoltz, M.-H., Giannikas, V., McFarlane, D., Strachan, J., Um, J., Srinivasan, R., 2017. Augmented reality in warehouse operations: Opportunities and barriers. *IFAC-PapersOnLine* 50 (1), 12979 – 12984, 20th IFAC World Congress.

URL <http://www.sciencedirect.com/science/article/pii/S2405896317324291>

Syberfeldt, A., Danielsson, O., Gustavsson, P., 2017. Augmented reality smart glasses in the smart factory: Product evaluation guidelines and review of available products. *IEEE Access* 5, 9118–9130.

Taulty, M., 2016. Windows 10, uwp, qr code scanning with zxing and hololens. Accessed: 2019-03-25.

URL <https://mtaulty.com/2016/12/28/windows-10-uwp-qr-code/-scanning-with-zxing-and-hololens>

Tompkins, J. A., White, J. A., Bozer, Y. A., Frazelle, E. H., Tanchoco, J. M. A., 2003. *Facilities planning*, 3rd Edition. John Wiley & Sons, Hoboken, N.J.

Uzun, Y., 2018. A small tip about display locked objects on hololens. <https://ujell.github.io/HoloLensFixedObjects/>, accessed: 2019-04-01.

Windows Mixed Reality Developer Forum, 2016. Fixed object in the camera/view. Accessed: 2019-04-10.

URL <https://forums.hololens.com/discussion/589/fixed-object-in-the-camera-view>

Wu, X., Haynes, M., Guo, A., Starner, T., 2016. A comparison of order picking methods augmented with weight checking error detection. In: *Proceedings of the 2016 ACM International Symposium on Wearable Computers. ISWC '16*. ACM, New York, NY, USA, pp. 144–147.

URL <http://doi.acm.org/10.1145/2971763.2971773>

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# Appendix **A**

## Parameters of each picking systems for the economic model

For each of the following table,  $n_R$  has been set to 100 rows per hour.

	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^j$	0,625	€/hour
Stock location unitary cost	$C_{SL}^j$	1,1	€/unit
Number of available stock locations	$n_{SL}$	2000	locations
Stock location devices total usage hours	$h_{SL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^j$	123,1818182	€/hour
Labour hourly cost	$C_{h,P}$	30	€/hour
Picker devices cost	$C_{d,P}^j$	2800	€
Picker devices total usage hours	$h_{d,P}$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$p^j$	25,74554817	rows/hour
Picking time	$t_{tot}^j$	139,83	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	19,83	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^j$	13,4515	€/hour
Error unitary cost	$C_E^j$	0,134515	€/unit
Labour hourly cost	$C_{h,P}$	30	€/hour
Sum of error proba*time	$\text{Sum}(p_{ei}^j * t_{ei}^j)$	16,1418	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e1	$p_{e1}^j$	0,045	
Probability of e2	$p_{e2}^j$	0,045	
Probability of e3	$p_{e3}^j$	0,045	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e1	$t_{e1}^j$	4,02	seconds
Time for e2	$t_{e2}^j$	39,66	seconds
Time for e3	$t_{e3}^j$	159,66	seconds
Time for e4	$t_{e4}^j$	139,83	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^j$	8,52	€/hour
Fixed costs	$C_F^j$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^j$	145,78	€/hour

Figure A.1: Parameters of the barcode handheld picking system. (Source: Battini et al. (2015))

	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^i$	0,738636364	€/hour
Stock location unitary cost	$C_{SL}^i$	1,3	€/unit
Number of available stock locations	$n_{SL}$	2000	locations
Stock location devices total usage hours	$h_{SL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^i$	123,2954545	€/hour
Labour hourly cost	$C_{h,P}$	30	€/hour
Picker devices cost	$C_{d,P}^i$	2900	€
Picker devices total usage hours	$h_{d,P}$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$p^j$	26,03225107	rows/hour
Picking time	$t_{tot}^j$	138,29	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	18,29	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^i$	13,09858333	€/hour
Error unitary cost	$C_E^i$	0,130985833	€/unit
Labour hourly cost	$C_{h,P}$	30	€/hour
Sum of error proba*time	$Sum(p_{ei}^j * t_{ei}^j)$	15,7183	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e1	$p_{e1}^j$	0,045	
Probability of e2	$p_{e2}^j$	0,045	
Probability of e3	$p_{e3}^j$	0,045	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e1	$t_{e1}^j$	2,48	seconds
Time for e2	$t_{e2}^j$	36,58	seconds
Time for e3	$t_{e3}^j$	156,58	seconds
Time for e4	$t_{e4}^j$	138,29	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^i$	8,52	€/hour
Fixed costs	$C_F^i$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^i$	145,66	€/hour

**Figure A.2:** Parameters of the RFID handheld picking system. (Source: Battini et al. (2015))

	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^j$	0,625	€/hour
Stock location unitary cost	$c_{sL}^j$	1,1	€/unit
Number of available stock locations	$n_{sL}$	2000	locations
Stock location devices total usage hours	$h_{sL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^j$	123,4090909	€/hour
Labour hourly cost	$c_{h,P}^j$	30	€/hour
Picker devices cost	$c_{d,P}^j$	3000	€
Picker devices total usage hours	$h_{d,P}^j$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$p^j$	26,48227159	rows/hour
Picking time	$t_{tot}^j$	135,94	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	15,94	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^j$	12,59266667	€/hour
Error unitary cost	$c_e^j$	0,125926667	€/unit
Labour hourly cost	$c_{h,P}^j$	30	€/hour
Sum of error proba*time	$\text{Sum}(p_{ei}^j * t_{ei}^j)$	15,112	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e1	$p_{e1}^j$	0,045	
Probability of e2	$p_{e2}^j$	0,045	
Probability of e3	$p_{e3}^j$	0,045	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e1	$t_{e1}^j$	1	seconds
Time for e2	$t_{e2}^j$	31,88	seconds
Time for e3	$t_{e3}^j$	151,88	seconds
Time for e4	$t_{e4}^j$	135,94	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^j$	8,52	€/hour
Fixed costs	$c_F^j$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^j$	145,15	€/hour

**Figure A.3:** Parameters of the pick-by-voice system. (Source: Battini et al. (2015))



	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^j$	28,40909091	€/hour
Stock location unitary cost	$C_{SL}^j$	50	€/unit
Number of available stock locations	$n_{SL}$	2000	locations
Stock location devices total usage hours	$h_{SL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^j$	123,1818182	€/hour
Labour hourly cost	$C_{h,P}$	30	€/hour
Picker devices cost	$C_{d,P}^j$	2800	€
Picker devices total usage hours	$h_{d,P}$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$p^j$	27,97420157	rows/hour
Picking time	$t_{tot}^j$	128,69	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	8,69	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^j$	7,65175	€/hour
Error unitary cost	$C_E^j$	0,0765175	€/unit
Labour hourly cost	$C_{h,P}$	30	€/hour
Sum of error proba*time	$\text{Sum}(p_{ei}^j * t_{ei}^j)$	9,1821	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e3	$p_{e3}^j$	0,02	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e3	$t_{e3}^j$	137,38	seconds
Time for e4	$t_{e4}^j$	128,69	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^j$	8,52	€/hour
Fixed costs	$C_F^j$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^j$	167,77	€/hour

**Figure A.4:** Parameters of the pick-by-light system. (Source: Battini et al. (2015))

	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^j$	12,67045455	€/hour
Stock location unitary cost	$c_{SL}^j$	22,3	€/unit
Number of available stock locations	$n_{SL}$	2000	locations
Stock location devices total usage hours	$h_{SL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^j$	122,9545455	€/hour
Labour hourly cost	$C_{h,P}$	30	€/hour
Picker devices cost	$c_{d,P}^j$	2600	€
Picker devices total usage hours	$h_{d,P}$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$\dot{p}^j$	28,1888654	rows/hour
Picking time	$t_{tot}^j$	127,71	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	7,71	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^j$	5,44975	€/hour
Error unitary cost	$c_E^j$	0,0544975	€/unit
Labour hourly cost	$C_{h,P}$	30	€/hour
Sum of error proba*time	$\text{Sum}(p_{ei}^j * t_{ei}^j)$	6,5397	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e2	$p_{e2}^j$	0,01	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e2	$t_{e2}^j$	15,42	seconds
Time for e4	$t_{e4}^j$	127,71	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^j$	8,52	€/hour
Fixed costs	$c_F^j$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^j$	149,60	€/hour

Figure A.5: Parameters of the RFID pick-by-light system. (Source: Battini et al. (2015))

	Notation	Value	Unit
<b>Stock locations hourly cost</b>	$C_{h,SL}^i$	0,625	€/hour
Stock location unitary cost	$c_{SL}^i$	1,1	€/unit
Number of available stock locations	$n_{SL}$	2000	locations
Stock location devices total usage hours	$h_{SL}$	3520	hours
<b>Picker hourly cost</b>	$C_{h,P}^i$	124,2045455	€/hour
Labour hourly cost	$c_{h,P}$	30	€/hour
Picker devices cost	$c_{d,P}^i$	3700	€
Picker devices total usage hours	$h_{d,P}$	3520	hours
Number of requested picking rows	$n_r$	100	rows/hour
Picking rate	$p^j$	27,76977897	rows/hour
Picking time	$t_{tot}^j$	129,63733	seconds
Travelling time	$t_{trav}$	120	seconds
Net picking time	$t_{net}^j$	9,63733	seconds
<b>Picking errors hourly cost</b>	$C_{h,E}^i$	11,34715492	€/hour
Error unitary cost	$c_E^i$	0,113471549	€/unit
Labour hourly cost	$c_{h,P}$	30	€/hour
Sum of error proba*time	$Sum(p_{ei}^j * t_{ei}^j)$	13,6165859	seconds
Error occurrence probability	$p_{ei}^j$	-	
Probability of e2	$p_{e2}^j$	0,045	
Probability of e3	$p_{e3}^j$	0,045	
Probability of e4	$p_{e4}^j$	0,05	
Error corresponding time	$t_{ei}^j$	-	seconds
Time for e2	$t_{e2}^j$	19,27466	seconds
Time for e3	$t_{e3}^j$	139,27466	seconds
Time for e4	$t_{e4}^j$	129,63733	seconds
<b>Fixed hourly cost</b>	$C_{h,F}^i$	8,52	€/hour
Fixed costs	$c_F^i$	30000	€
Fixed elements total usage hours	$h_F$	3520	hours
<b>Hourly cost function</b>	$C_h^i$	144,70	€/hour

Figure A.6: Parameters of the pick-by-vision system.

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# Appendix B

## Measurements from the test persons using the pick-by-vision system

Travel time
49,08
41,98
45,71
53,76
59,54
48,38
41,64
39,47
43,03
38,43
Average
46,102
ST Dev
6,688437452

Figure B.1: Travel time measurements

		Picking Time								
Picker	Picking list	1	2	3	4	5	6	7	Picking list order	Average per picker
	1	1	218,9	175,7	158,5	215,9	-	-	235,8	4,7,1,2,3
2	-	-	212,4	224,5	184,8	-	200,4	207,3	2,3,4,6,7	205,88
3	-	-	192,1	223,4	-	179,6	221	192,4	6,2,5,3,7	201,7
4	192,8	165,9	-	181,4	159,5	-	-	170,9	4,1,7,2,5	174,1
5	202,7	193,5	188	202,7	156,9	-	-	-	2,3,4,1,5	188,76
6	144,4	172,5	172,1	149,1	-	178,1	-	-	2,3,6,4,1	163,24
7	196,4	-	-	190,5	202,2	231,5	173,1	173,1	6,4,5,7,1	198,74
8	207,4	225,8	203	-	191,3	209,6	-	-	1,2,3,5,6	207,42
9	-	214,5	231	171,7	183,1	-	-	167,8	2,3,4,5,7	193,62
10	158	-	169,5	156,1	189,1	188,3	-	-	5,3,6,1,4	172,2

**Figure B.2:** Picking time measurements

Wrongs scans, e2							
Pick list Picker	1	2	3	4	5	6	7
1							1
2							
3							
4							
5							
6							
7							
8						3	
9							
10			1				

**Figure B.3:** Number of occurred type  $e_2$  error

Fault negative scans							
Pick list Picker	1	2	3	4	5	6	7
1			1				1
2		1				1	1
3			1				
4							
5					1		
6							
7	2						
8					2		
9		3	4		3		2
10	2					1	

**Figure B.4:** Number of occurred fault-negative scans

Error type  $e_3$  only occurred once for picker 10 on picking list 1 and error type  $e_4$  only occurred once for picker 3 on picking list 2.

