

ORDER PICKING SUPPORTED BY MOBILE COMPUTING

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To my son

Tom

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Contents

DEDICATION	v
ACKNOWLEDGEMENTS	vii
LIST OF TABLES	xv
LIST OF FIGURESxvii
SUMMARY	xxi
ZUSAMMENFASSUNG	xxiii
I INTRODUCTION	1
1.1 Contributions	1
1.2 Dissertation Organization	3
II ORDER PICKING	5
2.1 Order Picking Strategies	6
2.1.1 Batch Picking	7
2.1.2 Zone Picking	8
2.1.3 Further Strategies	9
2.2 Information Technology for Guiding the Order Picker	9
2.2.1 Paper Pick Lists	10
2.2.2 Pick Labels	10
2.2.3 Mobile Scanning Devices	10
2.2.4 Static Data Terminals	10
2.2.5 Pick-by-Voice	11
2.2.6 Pick-by-Light and Put-to-Light	11
2.2.7 Pick-by-Light Variants	11
III WEARABLE COMPUTERS AND INDUSTRIAL USAGE	13
3.1 Wearable Computers in Industry	14
3.2 Scientific Investigations to develop Wearable Computer Solutions for an Industrial Usage	14
3.3 Commercial Wearable Computing Solutions for Industrial Usage .	17

3.4	Conclusion	22
IV	BACKGROUND INFORMATION AND RELATED WORK	25
4.1	Wearable Computers for Order Picking	26
4.2	Visual-Based Picking Supported by Context Awareness	28
4.2.1	Improving the Experimental Procedure	28
V	COMPARING FOUR PICKING METHODS	31
5.1	Introduction	31
5.2	Experimental Design	32
5.2.1	Warehouse Layout and Task Description	32
5.2.2	Picking Methods	34
5.2.3	Environment	37
5.2.4	Method	38
5.3	Results	40
5.3.1	Performance Measures	41
5.3.2	Usability Measures	43
5.3.3	Timelines	46
5.4	Discussion	49
5.4.1	Evaluation of User Study Design	51
VI	USER-INTERFACE OPTIMIZATIONS	53
6.1	Introduction	53
6.2	Color Experiment	54
6.2.1	Picking Environment	54
6.2.2	Task Description	56
6.2.3	User Interface Variations	57
6.2.4	Method	59
6.2.5	Accuracy	60
6.2.6	Speed	62
6.2.7	Subjective measures	63
6.3	Context Experiment	64
6.3.1	Task Description	65

6.3.2	Method	66
6.3.3	Accuracy	67
6.3.4	Speed	68
6.3.5	Subjective Measures	69
6.4	Discussion	70
VII USAGE IN AN INDUSTRIAL ENVIRONMENT		73
7.1	Introduction	73
7.2	Difficulties in Planning and Preparing	74
7.3	Task and Picking Environment	74
7.4	Picking Methods	76
7.4.1	Pick-by-light	76
7.4.2	Pick-by-HMD	77
7.4.3	Pick-by-tablet	78
7.4.4	Pick-by-paper	78
7.5	User Interface and Variations	79
7.5.1	Pick step and Pick chart visualization	80
7.5.2	Picking procedure, pick- and put-visualization and shelf changes	81
7.5.3	Part Images	83
7.5.4	Optimization and audio feedback	83
7.6	Method	84
7.7	Accuracy	85
7.8	Speed	86
7.9	User Acceptance and User Feedback	88
7.9.1	Pick-by-HMD	89
7.9.2	Pick-by-tablet	90
7.9.3	Pick-by-paper	91
7.10	Discussion	91
VIII DISCUSSION		95
8.1	Connection and Summary of Studies	95
8.2	Goal and Hypotheses	99

8.3	Benefit-Cost Ratio	102
8.3.1	Investment Costs	102
8.3.2	Operating Costs	104
8.3.3	Performance	105
8.3.4	Conclusion	107
8.4	Further Observations and Lessons Learned	108
8.4.1	HMD characteristics for pick-by-HMD	108
8.4.2	Field-of-View, Resolution and Human Acuity with the SV-6	114
8.4.3	Becoming Accustomed to Using a HMD	116
8.4.4	Eye Dominance	118
8.4.5	Planning and Conducting an Industrial Study	119
IX	RECOMMENDATIONS FOR FUTURE WORK	123
9.1	Software and Hardware Developments	123
9.2	Controlled Studies	124
9.3	Industrial Case Studies	125
X	CONCLUSION	127
Appendix A	— STATEMENT OF MY OWN CONTRIBUTIONS AND CONTRIBUTIONS OF OTHERS	129
Appendix B	— INTERVIEW WITH CHRISTIAN BÜRKY	133
Appendix C	— FOUR CONDITION QUESTIONNAIRE	137
Appendix D	— OPTIMIZATIONS QUESTIONNAIRE	151
	REFERENCES	181
	Glossary	189

List of Tables

1	List of Likert scale statements.	39
2	Post-study rankings. A * indicates a significantly worse rank than the HMD.	44
3	Likert scale responses. A * indicates a significantly lower (worse) score than the HMD.	45
4	Ranking of conditions (lower values are better)	63
5	Ranking of context conditions (lower values are better)	69
6	Feedback from the question: “ <i>Did you like the use of images for the items to pick?</i> ”	69
7	NASA-TLX-Results	70
8	Comparison of the field of view of the virtual screen sizes of different HMDs and their occlusion of the field of vision. The images of the first line are shot with a fish-eye lens with a diagonal field of view of nearly 180°. The second line with a lens with a diagonal field of view of approximately 75°.	109
9	Weight and center of gravity of the HMD eyepieces while being connected to a holder for carrying the eyepiece. (During the measurements the connector cables are held so that their influence on the measurements is small. However, holding the cables causes minor fluctuations.)	112

List of Figures

1	teXXmo TX-1000 connected to a MicroOptical SV-6 and a rugged mouse from Vuzix	21
2	Visualization of Picking and Context information	29
3	Compared Methods	29
4	Arrangement of parts and shelves. Two sets of shelves, A and B, each contains 4 rows of 3 part bins.	32
5	Parts in the three order bins from a completed task.	33
6	The four picking methods. The same task is displayed with each method. The audio and HMD versions only show what is accessible to the picker while filling part of order 1 on shelf B.	34
7	View of people, parts, and equipment in the experimental setup . .	38
8	Time per task. A * indicates a significantly slower time than the HMD.	40
9	Comparison of the average time to complete each task per method .	42
10	Picking accuracy. A * represents a significantly higher number of errors than the HMD.	43
11	Overall task load	45
12	Timelines for each of the four picking methods	47
13	A participant uses two hands to collect parts while wearing a HMD.	50
14	Three shelving units	55
15	Wearable and HMD	55
16	Order bins	55
17	Part bins (colored modalites)	56
18	Modalities tested in the Color experiment	58
19	Mistakes/pick in Color experiment	61
20	Pick speeds of the different conditions relative to the average (1.00); lower is faster	63
21	A laser rangefinder detects the worker's hands as they pass the front plane of the shelving units. An explanation of the approach can be found in [26].	65
22	Interface showing pick (CI+LRF)	65
23	Interface showing wrong pick (CI+LRF)	66

24	Mistakes/pick in Context experiment	67
25	Pick speeds relative to the average (1.00) and normalized to the Color experiment (lower is faster)	68
26	The picking environment	74
27	Images from the picking environment	75
28	Pick-by-light	76
29	Pick-by-HMD	77
30	Pick-by-tablet	78
31	Pick-by-paper	79
32	First and final screen of a task	79
33	Shelf visualization	80
34	Pick-detection	81
35	Shelf change	82
36	Visualizations with object images	83
37	Comparison of the information presented to the user and the required input by a user (“>” indicates audio output; “<” indicates required user feedback (spoken))	101
38	Pick cart with Put-to-light prototype	105
39	The MicroOptical SV-6 can be positioned outside of the normal line of sight. Note that the field of view of the camera lens is nearly 180° (in the diagonal), which is higher than the field of vision of a human.	109
40	Look-around and see-through HMD in comparison (images are shot under same environmental lighting and with same exposure). Please note that the brightness of the environmental lighting has an impact on the readability of a see-through HMD. Head movements produce a moving background within the see-through HMD, which makes reading the see-through HMD more difficult.	110
41	Simulating different distances (with increasing distances from left to right) between the SV-6 eyepiece and the eye. In (a) the SV-6 is positioned very close to the eye with the effect that the eyepiece obscures more of the field of vision than necessary. In (c) the distance between the HMD eyepiece and the eye is approximately set to the eye relief of the HMD. Parts of the screen disappear when positioning the HMD eyepiece even further away from the eye (see (d)). Typically a distance between the ones simulated in (b) and (c) is used when working with the SV-6.	111

42	MicroOptical SV-6 with a field of view of about 18° showing an overlay of the square-wave grating acuity and blind spot results by Theodor Wertheim	114
43	Dimensions of Snellen acuity letter which a human with normal vision can read	115
44	This image roughly simulates the acuity a human with normal vision would have at the four edges of the shelf representation when fixating on the center of the shelf representation while using the MicroOptical SV-6 (Image was scaled down and back to its original size with XnView using the “ <i>Gaussian</i> ” setting)	116

SUMMARY

Order picking is the process of collecting items from stock and transporting them to a specific location. It represents one of the main activities performed in warehouses and accounts for about 60% of the total operational costs of a warehouse. About 750,000 warehouses worldwide distribute approximately 1 trillion USD in goods making order picking commercially relevant and of high interest for industry.

Often, a worker simply uses a paper pick list specifying the name, location, and amount of each item that needs to get picked for an order. While paper pick lists have the benefit of being flexible and requiring small investment costs, they have the drawback of being error-prone – especially in high density picking environments where multiple orders are picked in parallel (sort-while-picking).

In this dissertation I present the results of a newly developed mobile computing solution with reasonable investment costs that supports the picking process in a high density picking environment with multiple orders. The developed solution is presented on a head-mounted display (HMD). It has a graphical user interface that displays graphical representations of the shelves to pick from. Results show that in a high density picking environment, this solution is faster than paper-pick lists and pick-by-voice and virtually eliminates errors. Using color helps to identify the correct row and some evidence suggests that symbols and partial images as well as context feedback can further improve the error rate. Testing on an assembly line of an automobile manufacturer where normally pick-by-light was used showed some difficulty in user acceptance for HMDs. A tablet-PC mounted on the pick cart was well accepted in this study and may provide similar benefits and performance.

ZUSAMMENFASSUNG

Unter dem Begriff Kommissionierung versteht man das Zusammenstellen verschiedener Artikel nach vorgegebenen Aufträgen. Es ist eine der Hauptaktivitäten in einem Warenlager und ist verantwortlich für etwa 60% der Gesamtkosten. Es existieren etwa 750.000 Warenlager weltweit, die zusammen einen Absatz von ungefähr 1 Billionen USD haben. Dementsprechend ist die Kommissionierung kommerziell relevant und von großem Interesse für die Industrie.

Häufig wird von einem Kommissionierer lediglich eine Papierliste mit Namen, Standort und Anzahl der zu entnehmenden Artikel verwendet. Die Arbeit mit Papierlisten ist kostengünstig und flexibel. Sie hat jedoch den Nachteil, fehleranfällig zu sein – insbesondere, wenn eine hohe Kommissionierdichte vorliegt und wenn mehrere Aufträge parallel bearbeitet werden.

In dieser Dissertation präsentiere ich die Ergebnisse eines neu entwickelten “*mobile computing*”-Ansatzes mit angemessenen Investitionskosten, die den Kommissionierer in Umgebungen mit einer hohen Kommissionierdichte und parallel abzuarbeitenden Aufträgen unterstützt. Die entwickelte Lösung wird über ein HMD angezeigt und besitzt eine graphische Benutzerschnittstelle, die die Regale mit den zu kommissionierenden Artikeln graphisch visualisiert. Die Ergebnisse zeigen, dass bei einer hohen Kommissionierdichte diese Lösung schneller als eine textuelle Papierliste und Pick-by-Voice ist und Fehler nahezu eliminiert werden. Die Verwendung von Farben hilft, die richtige Reihe eines Artikels im Regal zu identifizieren, und es existieren Hinweise darauf, dass Symbole und Artikelbilder sowie Kontext-Feedback helfen, die Fehlerrate weiter zu minimieren. Eine Studie unter industriellen Bedingungen bei einem Automobilhersteller (wo normalerweise Pick-by-Light verwendet wird) zeigte, dass die Akzeptanz für ein HMD problematisch ist. Ein Tablet-PC, das an dem Kommissionierwagen befestigt war, wurde von den Kommissionierern besser akzeptiert und liefert ähnliche Vorteile und Leistungen.

Chapter I

INTRODUCTION

Order picking is the process of collecting items from stock and transporting them to a specific location. It represents one of the main activities performed in warehouses and accounts for about 60% of the total operational costs of a warehouse. About 750,000 warehouses worldwide distribute approximately 1 trillion USD in goods making order picking commercially relevant and of high interest for industry.

Often, a worker simply uses a paper pick list specifying the name, location, and amount of each item that needs to get picked for an order. While paper pick lists have the benefit of being flexible and requiring low investment costs, they have the drawback of being error-prone – especially in high density picking environments where multiple orders are picked in parallel (sort-while-picking).

One goal of this work was to develop a flexible mobile computing solution with reasonable investment costs which supports the order picker in a high density picking environment with multiple orders. Compared to text-based pick lists, this solution should result in a higher overall performance with regard to accuracy, speed and usability.

The primary hypothesis of the thesis was that in a high density picking environment, pickers using a graphical pick chart displayed on a heads-up display (HUD) will outperform pickers using a text-based pick list, a graphical paper-based pick list or pick-by-voice. Specifically, I evaluate picking speed, number of pick errors, and the picker’s subjective ratings.

1.1 Contributions

The topic of this dissertation is situated within the scientific field of Human Computer Interaction and mobile (wearable) computing. The primary contribution of

this work is the development of a mobile picking solution (with the pick-chart-based graphical user interface being the most important point of the solution), and the conducted studies with their corresponding papers. With the help of colleagues, I have evaluated the solution – with respect to speed, accuracy, usability and user acceptance – many times during the iterative development cycles, comparing it against different approved picking methods (paper pick lists, pick-by-voice and pick-by-light), comparing different extensions (context-feedback, audio-feedback, colors, symbols, images, different shelf transitions, sorting optimization, etc.) and different mobile solutions (a wearable computer connected to a HMD and a tablet-PC). Most studies were conducted under well controlled conditions with mostly inexperienced subjects (regarding order picking and HMDs), while the final study took place in an industrial environment under real working conditions with experienced order picking workers.

My contributions include:

- A method involving an easily reproducible order picking environment for quantitative user studies designed to compare different order picking solutions and different optimizations/variations of an order picking solution.
- The development of the concept of the pick chart for a fast and accurate interpretation of what (and how many items) to pick (and where to put them).
- A study showing the performance of the graphical pick chart in combination with a wearable computer connected to a monocular look-around HMD, compared to text-based paper pick lists, pick-by-voice, and graphical pick charts on paper.
- The development and evaluation of different extensions and optimizations of the pick chart including a visualization for using a pick- and put-detection.
- A qualitative evaluation of the deployment of the pick-chart-based solution

using a wearable computer connected to a HMD and a tablet-PC in an industrial order picking environment of an automobile plant under real working conditions with experienced workers comparing it against pick-by-light and paper pick lists.

- A consideration of the benefit-cost ratio for different scenarios.
- A survey of lessons learned from working with HMDs.

1.2 Dissertation Organization

This chapter attempts to give a detailed introduction to the topic and goal of the thesis. Chapter 2 will give an overview to order picking, also covering the currently most widely used picking methods in industry. Chapter 3 starts with a definition of a wearable computer and continues with a survey of wearable computers in industry. In Chapter 4 I discuss work related to my thesis. Chapters 5 - 7 cover previously published publications, and in Appendix A I state my own contributions and the contributions of others. Specifically, Chapter 5 compares the performance of a pick list presented graphically on a wearable computer with a HMD against the same graphical representation on a paper pick chart, a pick-by-voice system, and a text-based pick list. Chapter 6 evaluates extensions for the graphical pick chart and Chapter 7 compares the pick chart – on a wearable computer with a HMD and a tablet PC – against a text-based pick list and an established and highly efficient pick-by-light system. Chapter 8 starts with a short summary of the work and continues with a discussion of the results, considering the stated goal and hypothesis of this thesis. The Chapter continues with a consideration of the benefit-cost ratio regarding different picking scenarios and ends with discussing some further interesting observations and lessons learned during the work. Chapter 9 gives some suggestions for future work and Chapter 10 concludes the dissertation.

Chapter II

ORDER PICKING

Order picking is the process of collecting items from an assortment in inventory and represents one of the main activities performed in warehouses, accounting for about 55% [4] to 65% [18] of the total operational costs of a warehouse. According to Nave [45], depending on the branch of trade, order picking can even account for up to 70% of the warehouse and distribution costs and is the key for achieving customer satisfaction.

There is a wide variety of picking methods, ranging from fully automatic systems where thousands of objects are handled per hour, to relatively infrequent picks performed by hand from an inventory shelf. Most research papers in the field focus on more automatic systems [33], possibly because they are more amenable to analysis. Yet, most picking is still done manually, presumably due to the cost and difficulty of making a robotic system that can handle the large variety of parts typical in such tasks.

“Depending on the types of retrieval units, types of picks can be classified into pallet pick, case pick, and broken-case pick” [50], ranging from quantities where picking is done in multiples of full pallets (pallet pick also known as unit-load picking), multiples of cases (case pick), down to multiples of pieces (broken-case pick, also called piece pick). Broken-case pick is usually done from small load storage systems, for example, shelves with items stored in cartons or bins. The proposed solution of this thesis was developed with broken-case pick scenarios in mind but might be also of interest for case picking.

According to Tompkins [75], typically 50% of a picker’s time is spent traveling, 20% searching, 15% picking, 10% in setup, and 5% performing other tasks.

Research of manual picking systems focuses on optimizing travel time. Besides efficient path planning (which resembles the Traveling Salesman Problem [33]), orders requiring similar parts may be grouped together (proximity batching). Similarly, items that are normally picked together may be clustered on the shelves (family grouping). In order to avoid picker travel, automation may bring shelves of items to the picker based on the requirements of the order, resulting in a very small pick area. In this thesis I focus on optimizing the presentation of pick lists to improve setup, search, pick times, and accuracy.

Typically, order picking begins with a paper picking list specifying the location of each type of item, the number of items to be picked, and the sequence in which the items will be picked. A worker collects the items from stock and transports the items to a specific location for later delivery to a customer or to an assembly line. Errors in picking can jeopardize customer relations or stop an assembly line. Thus, while picking should be time efficient, it should also be accurate.

2.1 Order Picking Strategies

In this thesis, only manual order picking systems (employing humans) are of interest. In this category most of the picking is done by the picker-to-parts principle, where the order picker walks or drives along the aisles to pick items [33, p. 5] (also called picker-to-stock [50]). Another category is a parts-to-picker (or stock-to-picker) system where the required parts are transported to the picker. Due to the high costs of such systems, these are also not examined within this dissertation. According to de Koster et al., picker-to-parts systems can be distinguished into low-level and high-level systems. In low-level systems the order picker picks the items while traveling along the storage aisles. In high-level systems order pickers travel on board a lifting order-pick truck or crane along high storage racks. According to an estimate by de Koster et al. [33, p. 6], 80% of the warehouses in Western Europe use low-level picker-to-parts systems, and the suggested solution of this dissertation is intended and evaluated for this type of order picking systems

though it might also be used for high-level systems.

As stated in the introduction, the proposed solution of this thesis is aimed for high picking densities where many picks from different pick locations are required within a shelf. While the proposed solution is also usable in low density picking environments, only a small improvement can be expected by switching from paper pick lists to a mobile pick-chart-based solution (low complexity will keep errors low even with paper pick lists, and walking will dominate picking). Below I discuss two common techniques – *Batch Picking* and *Zone Picking* – which could be applied to existing picking systems to increase the order picking performance and picking density. As the mobile pick-chart-based solutions can handle very complex pick tasks with very low error rates, such techniques could be introduced in combination with it.

2.1.1 Batch Picking

Picking density can be increased (and the required travel time reduced) by changing from single order picking to batch picking (e.g., increasing the number of orders performed at once). For batch picking (also called multi-order picking) multiple orders are picked in parallel by just one order picker. Items can either be sorted to their corresponding orders during the picking process (sort-while-picking) or items can be sorted to their corresponding orders in a separate sorting step after the picking is finished (pick-and-sort, also called sort-after-picking).

Batch picking with sort-while-picking can often be easily realized and is explicitly supported by the proposed solution. For the hardware, only a pick cart with separated locations for the orders is required. A limitation regarding the number of orders that can be handled in parallel might result from the available width of the aisle and the required space for the orders. Another limitation regarding batch picking (independent of sort-while-picking or pick-and-sort) is the available time to gather orders for clustering. The simplest strategy to cluster orders is by clustering in the arriving sequence of orders (also called time window batching). A common and often more efficient strategy is to cluster by similar orders requiring

the same parts or parts with close locations (proximity batching). However, if orders are required to have a given sequence – common if picked orders are required at an assembly line – such a strategy would require an additional step to restore the correct sequence of orders.

2.1.2 Zone Picking

Introducing multiple zones (also called zoning) is another common technique that can be used to increase the performance of order picking systems. In this case, the whole pick area is divided into a number of smaller areas¹. Zones can be processed in a progressive manner (the order is passed from one zone to the next, also called pick-and-pass) or in a synchronized manner (the order is performed in parallel in all zones and finally is brought together, also called wave picking). The following list highlights some benefits of multiple zones resulting in an increased picking density:

- Zone picking can be used to reduce the required space for the items on a pick cart (if the picked items of a zone get placed into the corresponding order boxes in a separate step, the required space for the orders on the pick cart only needs to be of the size to keep all items of the corresponding zone) and thus allow more orders to be performed in parallel.
- Orders that do not require any items within a zone can pass these zones so that only orders that require picks within a zone need to be carried along on the pick cart.
- An optimized clustering of orders within each zone can be achieved when using multiple zones in combination with proximity batching.

¹Zoning does not require a physical separation into zones and strategies exist where the zone sizes get dynamically adjusted.

2.1.3 Further Strategies

Routing strategies, layout and storage are other possibilities to decrease the required travel times and thus to increase picking density. Items that are normally picked together may be clustered on the shelves (family grouping) or items may be randomly distributed on multiple locations within the warehouse. In this thesis, I assume that a useful layout and storage strategy is already applied in the warehouse. Finding optimal routes should not only take into account the shortest possible path (which would resemble a special case of the Traveling Salesman Problem) but also aspects like aisle congestion, the required time for turning a pick cart, and the preference of order pickers (it has been shown that the optimal route often appears to be illogical or suboptimal to the order pickers). Therefore, *“usually a simple and standardized routing rule is preferable in practice”* [37, p. 21], and in this thesis I assume that a routing rule for the picking line is externally defined.

2.2 *Information Technology for Guiding the Order Picker*

In this section I will describe the most commonly used information technologies for guiding the order picker. The information technology needs to tell the order picker which and how many items to pick for a particular order. The information technology should present the required information in a way that picking errors are kept low while allowing a fast picking process. User acceptance and the required investment- and operating costs are important factors in choosing the most suitable information technology for a particular picking zone. Other factors may include the possibility for a real-time inventory during the picking process or flexibility regarding required changes in the storage. As conditions differ between warehouses and picking zones, there is no single information technology that can be seen as the generally best solution.

2.2.1 Paper Pick Lists

Picking with paper pick lists is still the most widely used method for order picking [68, p. 47]. The big advantage of paper pick lists are the low investment costs (and their high flexibility if the warehouse layout or storage needs to be changed). The biggest drawback of paper pick lists, however, is the high error rate.

2.2.2 Pick Labels

A less common form of paper-based picking systems are pick labels where a label is printed for every required pick location. According to Detlef Spee [68, p. 53] the error rates are better than for paper pick lists but higher than with paperless picking systems.

2.2.3 Mobile Scanning Devices

Mobile scanning devices equipped with RF or bar code scanning technology are commonly used for order picking. Typically the next pick location and the required number of items is shown in text to the order picker. The order picker confirms his pick by scanning the corresponding tag and then is shown the next instructions automatically. Compared to paper-based picking solutions this procedure reduces the chance for errors. Picking with mobile scanning devices is relatively slow due to the scanning process, and typical handheld devices are difficult to handle. Wrist-worn devices with ring bar code scanners (see also Section 4.1) reduce the amount of equipment that needs to be carried but still can obstruct the order picker during the picking process.

2.2.4 Static Data Terminals

In parts-to-picker systems, static data terminals can be used instead of a mobile scanning device. Typically a normal personal computer is used with a bar code or RF scanner.

2.2.5 Pick-by-Voice

Pick-by-voice wearable computer systems (see also Section 4.1) cue the picker as to the next pick and free the picker’s hands for manipulating the items [71]. Such systems typically use speech recognition for the picker to give commands such as “*next pick*”, “*repeat*”, “*back*”, or “*empty*” to indicate that the item was not where it was expected. Some systems also require that the order picker speaks a check value instead of a command like “*ok*” to confirm a pick. This technique helps to avoid picks from an incorrect location. As the required audio in- and output requires a certain amount of time, these systems are best suited in warehouses where a worker must travel between the picks and where the commands are played while the order picker is traveling.

2.2.6 Pick-by-Light and Put-to-Light

If there are frequently many items to be picked within just one shelving unit, pick-by-light is an appropriate picking method to achieve a high picking speed and low error rates. Lights mounted under or over each pick location – and under or over the order bins, if multiple orders are being picked at the same time (called put-to-light) – indicate which parts to pick or put, and buttons next to the lights are used to confirm a pick or put [5]. Some systems also offer proximity sensors or laser scanners to confirm the picks and puts of a worker [60]. However, pick-by-light systems require a high initial investment, making them often only economical in areas with smaller items and high turnover rates.

2.2.7 Pick-by-Light Variants

This section presents some new, but yet not widely used pick-by-light variants. These may be either prototypes or demonstrators developed within a scientific project or newly developed methods which have already been sold commercially for a short time.

Pick-by-light can also be implemented using projectors or lasers mounted on a ceiling or wall, though such systems can be difficult to deploy in practice as the

picker may often obscure the beam while performing his tasks.

If the pick cart is moved on tracks and offers a localization of the position, static light beams (attached for all existing row heights, and for both aisle sides) can be switched on (and off) at the correct moment to indicate a required pick.

A pick cart prototype with a moving laser projector has been developed by the AVILUS project. By determining the orientation and position of the pick cart, the laser projector can be adjusted to project directly onto the next pick location [62, p. 106].

Chapter III

WEARABLE COMPUTERS AND INDUSTRIAL USAGE

In my thesis, I define a wearable computer as a device that is worn by the user while in operation and enables unencumbered use. Hence, a wearable computer should be designed (in combination with a customized user interface) to support the user performing a primary task – like order picking – in a non-distracting way. Accordingly, Starner wrote in [70] “*Wearable interfaces must be adapted to a wearer’s environment and task instead of using default desktop interfaces. A heuristic is that a wearable interface should be designed to maximize performance and minimize investment in attention.*”¹

In [49] Oulasvirta et al. describe how mobility tasks, such as walking around and monitoring for passersby, compete for cognitive resources with other tasks, including mobile human computer interaction tasks. In our scenario these tasks include: moving the pick cart, searching for the correct part bin, picking the parts and placing the parts into the correct order bin. All these tasks require a visual perception of the environment and thus compete with a task like reading from a HMD. According to Oulasvirta [48], designers should keep the required interaction units as short as possible and in his doctoral thesis Ashbrook [3] defines “*interactions with a device that take less than four seconds to initiate and complete*” as *microinteractions*.

Our user interface is designed to allow the user to quickly perceive the required items to pick. If used with a wearable computer and a HMD the user can glance at the HMD while both hands are free to be used for the primary task.

¹Further definitions of wearable computers can be found in the doctoral thesis of Witt [80, pp. 11–14].

3.1 Wearable Computers in Industry

For more than a decade, wearable computing systems have been expected to revolutionize many industrial work processes by improving performance and quality. Research from the International Data Corporation (IDC) in 1999, for example, estimated the U.S. demand for wearable computers in the industrial, manufacturing, military, government, and medical sectors would be 600 million USD by 2003 [2]. Based on these expectations, many research projects had a goal of developing wearable computer (or augmented reality (AR)) prototypes for industrial scenarios². While some of these prototypes showed potential for use in industrial environments, only a very few wearable solutions have been commercially successful. In this section I start with scientific investigations to develop wearable computer solutions for a industrial use followed by a few commercially available solutions.³

3.2 Scientific Investigations to develop Wearable Computer Solutions for an Industrial Usage

The fields of wearable and ubiquitous computing have evolved from the creation of laboratory prototypes to examining systems deployed in workers' and consumers' everyday lives. Researchers focused on the tasks of inspection, maintenance, manufacturing, repair, and training as potential areas where wearable computing might prove beneficial.

One early approach was Mizell's AR task of assembling wire bundles for aircraft by augmenting the real scene with assembly annotations. The project started in 1989, and in his last publication regarding the wire bundles project [42], Mizell stated that the technology was in the process of being adopted for the production line. Unfortunately, he later discovered that the system was never actually used

²WearIT@Work, SiWear, ARVIKA, ARTESAS and AVILUS to name some of the projects within Germany and Europe

³I will not cover Military and emergency tasks as these applications are usually different from industrial scenarios (for example, users might be more willing to carry a wearable computer solution if this might save their lives).

in production (personal communication with T. Starner, September 26, 2012).

Siewiorek, Smailagic and Starner provide an overview of user studies of deployed prototypes in different areas [64]. Two prototypes that showed valuable improvement compared to the same practice without a wearable computer described in this work are the VuMan 3 and Navigator 2 from the Carnegie Mellon University (CMU)⁴. The VuMan 3 was used as an electronic checklist with 600 items for an inspection of amphibious tractors. It used a HMD and a rotary dial input device. One of the big benefits of the VuMan 3 compared to the paper checklist was the fact that the VuMan 3 could be used while working in positions (such as laying under the vehicle looking up at the bottom of it) where reading and writing on a clipboard was too uncomfortable and thus required extra movements (crawling back and forth to get into position for the inspection and to get into a more comfortable position for reading and writing on the checklist). Inspection time was reduced by 40%. With the time saved eliminating entering the hand-written text into a computer, the total time savings was 70%. Additionally, the VuMan 3 reduced the maintenance crew from two people to one. The Navigator 2 had integrated speech input and was evaluated for different applications such as the assembly of wire harnesses in airplanes and the inspection of airplanes. In the wire harness scenario, the worker reads an identification from its bar code. Afterwards, using augmented reality technology, the defined route of the corresponding wire is superimposed on the Navigator’s display. Time trial evaluations indicated savings of 25% compared to paper instruction lists. In their work Siewiorek, Smailagic and Starner also report the lessons learned from these prototypes. For example, Georgia Tech’s small airplane inspection experiments showed that the wearable interface can significantly interfere with experts’ natural abilities [47]. Simple changes to the airplane inspection interface, such as allowing the user to see inspection steps in logical “chunks,” improved performance. Similarly, Lawo,

⁴For a comprehensive overview of the different wearable computers and applications developed at CMU please refer to the following publications by Smailagic and Siewiorek [65, 66].

Herzog and Witt, reported a reduction in task performance and learning productivity when first testing a wearable computer-based system for the assembly of mechanical parts. Heavy use of context sensing was required for the wearable system to perform similarly to a paper solution [36]. The work presented in their paper was part of the wearIT@work project. It tested the use of wearable computing in different industrial scenarios [52]. The project started in 2004 with 42 partners (with the TZI as project coordinator) and had a duration of five years with a project volume of about 23.7 million Euro. Prototypes were developed and tested in four pilot applications: aircraft maintenance (at the European Defence and Space Company, EADS), car production (at Skoda Auto division), health-care (at GESPAG, an Austrian hospital operator), and emergency response (at the Paris Fire Brigade). The project showed that wearable technology has the long-term potential to change the out-of-office workplace just as much as personal computers changed the office environment [38]. We have not yet achieved this impact of wearable computing for industry. Another industrial wearable computing project at the TZI was Winspect [11]. In this project, a prototype glove was used as an input device together with a wearable computer connected to a HMD for the inspection of steel cranes.

Regenbrecht et al. (who have been involved in the ARVIKA project [22]), wrote a survey on augmented reality projects in automotive and aerospace industries [58] reporting the results and lessons learned from ten different augmented reality projects. Again one of the projects dealt with wire bundles, similar to Mizell's Boeing project and the wire harnesses project with the Navigator 2. However, the aim of this project was to measure the required length for the wire bundles with the help of an augmented reality system. In the conclusion regarding this project the authors wrote: *“While the software was well received by the users, it has two main shortcomings. First, the tracking systems used [sic] require too much instrumentation of the environment and are too sensitive for the harsh environment (lighting conditions, vibrations, possible collisions with objects or persons).*

Second, the display technology used is neither robust enough nor ergonomically designed for extended use. A rugged (large) monitor solution does not give the impression of working inside the girder. The HMD solution is too obtrusive and a projection approach is impossible due to the black girder surface or too difficult to integrate into the working environment (for example, a laser)." Considering all projects, Regenbrecht et al. state that augmented reality technology has not yet reached a level of maturity that allows for a widespread deployment from scratch but that in a midterm perspective, augmented reality is on its way to become a productive tool in industry.

Of course, there have been many more wearable computing projects where industrial scenarios were evaluated. In the interview conducted with Christian Bürgy at the *International Symposium on Wearables Computers* (ISWC) in 2012, he mentioned the projects he was involved in and where he worked in cooperation with Bosch for a speech-controlled wearable computer supporting inspections in garages [13, 15].⁵ Further mentions of industrial wearable computing projects can be found in the doctoral thesis of Bürgy [14, pp. 82–130] and a recent journal article from Aleksy and Rissanen [1].

3.3 Commercial Wearable Computing Solutions for Industrial Usage

The two most successful wearable computing solutions I have found in my literature search that have had a long and continued success in industry are used for order picking: Motorola's Wrist Computer, which utilizes a ring scanner worn on a finger, and Vocollect's Pick-by-Voice system. Both solutions will be discussed in Section 4.1.

In his article "*Wearable Computing Goes Live in Industry*", Stanford [69] focuses on a "*wearable solution*" from ViA Incorporated consisting of a central computer unit connected to a modular touch screen worn in a tool belt. The

⁵The full interview can be found in Appendix B.

system runs ViA's shipyard inspection application. This solution was used at Bath Iron Works (BIW), a shipbuilder in Bath, Maine where an 80-to-1 return on investment over a three-year amortization period was realized. *"That 8,000-percent return resulted from 70-percent reductions in inspection times, created because connected wearables reduced average information delivery times from two or three hours to about 20 minutes."* On the application side, Standford names different applications that were used with the ViA wearable computer at BIW including a virtual test equipment system providing an oscilloscope and multimeter, and a virtual maintenance system including a *"communication system that sends voice, video, and still images of various resolutions to remote experts and displays Interactive Electronic Technical Manuals"*. The continual reduction in size of electronics, including chips and processors, has ended the market for these kinds of devices, as current tablet-PCs can be built small enough that a modular touchscreen with a separate computer unit would not make any sense. However, with the definition of a wearable computer given at the beginning of this Chapter 3 – *"I define a wearable computer as a device that is worn by the user while in operation and enables unencumbered use"* – it is controversial if the concept of ViA's *"wearable computer"* (or a tablet-PC) is a wearable computer. Even with a mechanism to carry the tablet-PC (or modular touchscreen) hands free, in most scenarios it will interfere with the primary task flow, as it needs to be held in the hands to read the informations shown on the display.

Computer Products & Services, Incorporated was founded in 1990 and in 1996 they changed their name to Xybernaut Corporation [53] and went public. In many news releases Xybernaut was stated as the *"leading provider of wearable computing hardware, software and services, bringing communications and full-function computing power in a hands-free design to people when and where they need it."* With the expectation that wearable computers would revolutionize many industrial work processes and that wearable computers will become a highly profitable market, Xybernaut invested heavily in development and was in cooperation with

IBM regarding IBM's speech technologies [54] and later also regarding the MA V which was manufactured by IBM [81]. In 2000, Xybernaut, IBM Canada, and Bell Canada launched a joint large-scale trial application of wearable computers [55]. In 2001, in another News Release [10] Bell Canada announced: *“As a result of a successful market trial, Bell Canada is purchasing 300 of the MA V, the latest version of Xybernaut's wearable computers. The devices will eventually replace the existing IBM ThinkPad laptops that are used in the field by approximately 10,000 Bell Canada technicians. The MA V combines next generation mobile computing with next generation wireless technology, enabling mobile workers to perform technical functions on-the-go. The wearable computer can be worn as a vest or belt and is equipped with either a head-mounted or a flat panel display screen for viewing images. ... Bell Canada service technicians found the technology easy to use and a valuable tool. Time savings resulting from improved portability and reduced computing time was more than 50 minutes per day per technician.”* According to an article by the *The New York Times* [23], Bell Canada technicians who tried both the HMD and the flat panel display preferred the flat panel display hooked onto belts or vests. *“We do a lot of climbing, or going through forests with branches hanging down ... The way the headset sat, it stuck out and got in the way.” ... “Technicians who work in one place – like cable specialists – did not have as many problems with the HMDs.”* Another case study about the use of the Xybernaut wearable MA V (with a flat panel display) for asbestos management can be found from Sitemaster [25].

As the market for wearable computers did not grow as expected, Xybernaut was unable to sell as many wearable computers as anticipated. In 2003, they backed out of a deal to pay IBM \$50 million to build 24,000 of its devices [40]. In 2004, Xybernaut reported a nine-month revenue increases of 51% with \$11,019,887 surpassing their previous annual record. Within this three quarters, however, they had a net loss of \$12,497,573 [16]. According to a column by the *The Washington Post* from 2005 [31], Xybernaut *“has sold fewer than 10,000 of its purse-size*

computers” and lost \$162 million over the years. The article also reports criminal charges that have been filed against three principals of Xybernaut accused of defrauding investors out of \$16.8 million in the sale of Xybernaut stock. In July 2005, Xybernaut filed for bankruptcy reorganization and was able to emerge from bankruptcy protection on Dec. 31, 2006 [20]. However, since there is no indication of any notable success.

The MicroOptical Corporation was founded in 1995 and sold a few different HMDs including the SV-6 (see Figure 1) which we used in most of our studies. Mark Spitzer, formerly CEO/CTO of MicroOptical, which was later re-branded as Myvu, reported in a personal communication information about performed case studies in the medical sector. *“The SV6 device was used extensively for beating heart surgery, vessel harvesting, and neurosurgery by two surgeons who came to us with their outstanding successes.”* The neurosurgeon *“liked having medical images (CT scans, MRI) right above his surgical loops. This way he could reference the image to refresh his memory without removing his head to look at a CRT. In order to move his head, he would first have to remove his hands from the operative field. With the SV6, no head motion was needed. If he needed the full resolution of the MRI or CT image, he could remove his hands then look at the full image; however, this was often unnecessary. A 9 hour removal of a brain tumor could be reduced to a 6 hour operation by using the SV6.”* The Thoracic surgeon used the SV-6 for a beating heart bypass surgery, *“in which the patient was not on a heart-lung machine. It was often necessary to have instant reference to vital signs and the SV6 positioned above the surgical loops made this possible. He also used the SV6 for imaging during vein harvesting.”* *“Commercialization of the device was more of a business issue than a technology or product issue. We found that medical distribution channels were very difficult for a small company. ... So in the end we gave up medical markets even though we had convincing case studies showing the product was successful in the operating room.”*

“In 2005, teXXmo was founded in Böblingen⁶, as a sort of management buy-out of Xybernaut GmbH, a 100-percent subsidiary of the Xybernaut Corporation.” Under the SiWear project they developed the TX-1000 wearable computer (see Figure 1) and now offer its successor, the teXXmo ONE [76]. In the interview

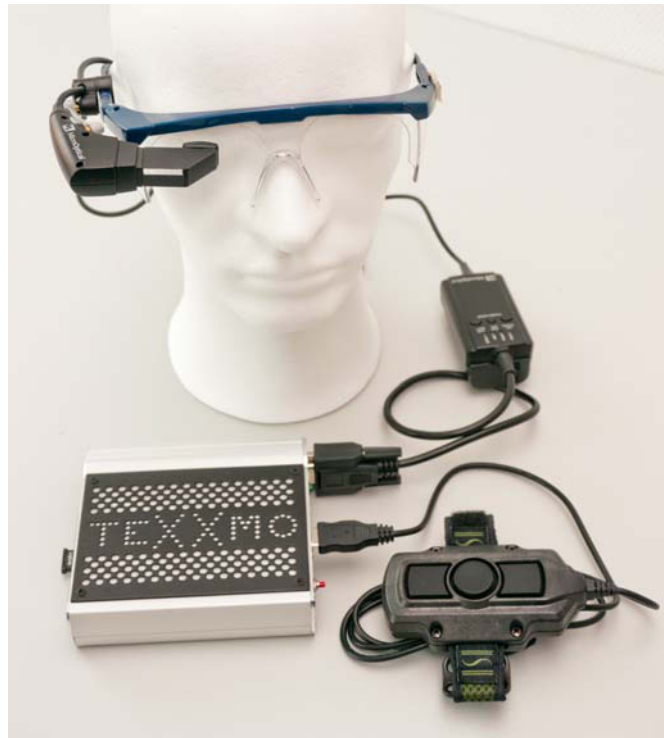


Figure 1: teXXmo TX-1000 connected to a MicroOptical SV-6 and a rugged mouse from Vuzix

that I did with Christian Bürgy at ISWC 2012 he stated: *“Our daily business is distribution of industrial-grade Tablet PCs. We built up a brand and do quite well. Wearable computing is an R&D topic, which we follow in various research projects, and we introduced a mini-series of a commercially wearable computer system, which mostly serves pilot and university projects.”*

Another wearable computer developed by SN Technics was presented in 2006. In a prospectus published by Kontron [32] the wearable computer is described as a *“borrowed eye on site”*. The wearable computer is worn on a belt and connected to a camera, microphone and HMD and supports a bidirectional communication. Jörg Seitz, at the time development manager from SNTechnics is cited in the

⁶located in the south of Germany

prospectus: “Coupled with the new camera technology we were able to take from medical technology, for the first time a solution is available that is interesting not just to early adaptors, but which will provide wide circulation,” Although there were pilot projects with Bosch, Daimler-Chrysler, DMG, and Miele, the company SN Technics does not exist anymore. I found no indication for a successful dissemination of the i-boro solution in the industry.

Currently industry offers different wearable computing solutions with HMDs developed for remote service. These include: TRAVIS Callisto from Brückner [12], NEC Tele Scouter⁷[46], and KNAPP - KiSoft Web Eye [30]. KNAPP offers the same wearable hardware for their augmented reality order picking solution called KiSoft Vision [29] (see also Section 4.1). Without any meaningful success so far, the future will show if these solutions will be more successful than their predecessors.

Another wearable computer is the Golden-i from Kopin [74], which is currently only sold as a developer kit. In contrast to the previously stated wearable computers, the Golden-i is completely worn on the head, uses an ARM processor, and runs Windows Embedded CE 6.0. Kopin plans to release a revised version for market sales.

3.4 Conclusion

While Motorola’s wrist computer and Vocollect’s voice controlled wearable computer are a success, I have not found any commercially available wearable computer using a HMD that has had a long lasting success in an industrial environment.⁸ In the interview with Christian Bürge I asked him why he thinks that HMDs have not been very successful in industrial scenarios yet. He answered, “*Price and weight are still too high! And none of the HMDs have been really ruggedized and*

⁷Using the Brother AirScouter as HMD. Recently only sold in Japan but taking markets outside of Japan into consideration

⁸As already stated, I exclude military usage and I share the statement of Bürge he gave in the interview that the preconditions in a military scenario are different: “*Money seems to be less of an issue and with all the equipment soldiers have to carry anyway, the weight of a HMD seems neglectable; besides that: the motivation to save lives might help to overcome usability issues.*”

durable.” I agree with this estimation but also think that from the usability and user acceptance point of view it is not just weight and ruggedness but also other factors like the overall wearing comfort, the obstruction of the users field of vision and the initial difficulties many workers have when they try to read from a HMD (Section 8.4 discusses these and other issues in more detail).

Aleksy and Rissanen [1] point out another problem. To them predictability is the main problem. *“Predictability has a key role in investment decisions when considering of applying new technology. It is difficult to convince for example a manager of process automation service to invest \$4,000 in a head-mounted display (HMD) for each of his 2,000 service engineers which would make a total cost of 8 million dollars if there is a risk of not improving the overall efficiency in the organization. Wearable computing has still not really been proven to provide adequate ergonomics, technical reliability and general practicality in a way plant management would not have any doubts about. Cost-efficiency drives the industry.”* ... *“According to the results of our literature review, many authors identified the potential of wearable computing to gain efficiency improvements in industrial applications. This fact is proved by plenty of publications. However, there is still a lack of comprehensive case study results emphasizing the benefit of wearable computing in this area.”*

Recently, technology advances have begun to reduce some of the limitations of wearable computers. With current technology and powerful and efficient processors, the computing unit and battery can be small enough to be comfortably worn. The 21 gram Android (and Ubuntu) stick developed by FXI and Google Project Glass are examples. However, most currently available HMDs are too heavy (with a center of gravity too far off-center) to be comfortably worn. Others distract too much from the normal field of vision. Robustness, durability, and costs are further factors. With current developments – like Project Glass from Google – user acceptance and the envisioned benefit of prospective users will increase which will also give wearable computers with HMDs better chances to succeed in industrial

markets. The last hurdle after improved HMDs will be the required accustomization that is needed for reading from a HMD. In a midterm perspective, I expect that there will be a market for HMDs for industrial use, just not as big as once expected.

Chapter IV

BACKGROUND INFORMATION AND RELATED WORK

The topic of this dissertation arose from the project SiWear¹, funded by the German Federal Ministry of Economics and Technology within the program SimoBIT². The acronym SiWear stands for “*Sichere **W**earable-Systeme zur Kommissionierung industrieller Güter sowie für Diagnose, Wartung und Reparatur*” or translated: “*Secure wearable-systems for order picking of industrial goods and also diagnosis, maintenance and repair*”. The project started in 2007 and had a duration of three years. SAP was project leader, other partners were: Daimler, Mobile Research Center (MRC), NEO Business Partners and teXXmo.

My thesis concentrates on the development of a wearable, respectively mobile solution that supports the order picking process. One of the aims of the project was to evaluate the developed solutions in a plant of Daimler, a huge automotive company. In these plants, as with most plants and warehouses, order picking is often still done with paper pick lists. However, paper pick lists have the disadvantage of being error-prone. In some of Daimler’s picking lines, pick-by-light improved the picking performance (reducing picking times and errors). But a pick-by-light setup requires a high effort and is expensive, making it uneconomical in many picking lines. While pick-by-voice is known to achieve low error-rates, in many of the high density picking lines at Daimler, it proved to be relatively slow. Additionally, high environmental noise levels often make the use of pick-by-voice in the Daimler plants ineffective.

I am working as a research assistant at the TZI (Center for Computing and

¹<http://www.siwear.de>

²<http://www.simobit.de>

Communication Technologies). The TZI is an institute of the University of Bremen and was also project partner of the SiWear project.³ I started work for the SiWear project in 2009. While there were some pilot studies previously, the first major study was conducted in 2009, which was published by H. Iben, H. Baumann, T. Starner, C. Rutenbeck and T. Klug [27].

4.1 Wearable Computers for Order Picking

Symbol Technologies created a wrist computer (WSS 1000) with a ring bar code scanner worn on a finger (RS-1) that frees both hands and speeds package scanning and inventory control compared to handheld devices (see also Section 2.2.3). Stein et al. [72] discuss the development of the device with a focus on user ergonomics: *“Good ergonomics is essential for any commercially available wearable computer product. If not designed so it can be worn comfortably and safely for a ten-hour shift, the user is likely to refuse to wear the system, or use it improperly.”* According to Stein et al., the final product was released in September 1996 with 17,000 units being shipped to UPS that month. In the article, *Wearable Computers: No Longer Science Fiction* [71], Starner wrote about the wrist computer, *“the resulting product is a notable success, providing the company with a unique differentiator and profitable new markets. ... They are often used in warehouse receiving and picking, shelf inventory, point-of-sale checkout, package tracking, baggage handling, and parts assembly.”* In the article from 2002, Starner wrote that Symbol spent over 5 million USD to develop the device and sold about 100,000 units.

Symbol was acquired by Motorola, and the current successor of the WSS 1000, the WT4090 and RS409 Ring Scanner (WT4000 Series), are successfully used in many companies. In a case study at Ben E. Keith [43], error ratio improved from 1 in 1500 with paper pick lists to 1 in 16000 with the Motorola wrist computer and the ring bar code scanner in combination with the SAE Selector Pro Software.

³The TZI belonged to the research association MRC

In their case study they also report speed improvements on the individual level: “*Most of us can pull 250 cases an hour with this product; it makes it just that easy.*” According to January, the director of Process Improvement at Ben E. Keith, they were able to get their full return on investment within six months.

Vocollect developed a pick-by-voice solution for inventory picking using their speech-only interface [71] (as described in Section 2.2.5). According to a case study, pick-by-voice increased picking speed by 8 to 15% compared to mobile scanning devices and by 3 to 4% compared to paper pick lists [41]. While the overall accuracy increased from 99.52 to 99.64%, no concrete data is given how this increase is differentiated between previous accuracy values of paper pick lists and mobile scanning devices. According to Starner, “*as of December 2000, Vocollect had approximately 15,000 users and revenues between US \$10 and \$25 million.*” Meanwhile, pick-by-voice from Vocollect (now a business unit of Intermecc) is offered by many large companies in the warehouse business.

The Institute for *Materials Handling, Material Flow, Logistics (fml)* from the *Technische Universität München (TUM)* has begun to use HMDs to assist order picking with their *Pick-by-Vision* project. Schwerdtfeger et al. [63] compared two options which used a HMD: a graphical 2D representation of the shelf and an augmented reality solution and benchmarked them against a textual pick list. In this study, neither the graphical 2D representation nor the augmented reality solution showed a significant improvement over the textual pick list. Later Reif et al. [59] created an augmented reality *pick-by-vision* system to guide the picker to each item using arrows and *attention tunnels*. These tunnels are overlaid on the user’s visual field as they traverse the pick area. Pick speed increased by 3.7% over a paper list, but pick accuracy did not show a statistically significant improvement. This system, however, seems to be more appropriate in picking environments where a worker needs to travel between the picks. Recently, the company KNAPP also started to offer a HMD-based augmented reality system for order picking [29].

In contrast, our solution – using a graphical pick chart, as described in Chapters 5 - 7 – does not rely on augmented reality. As a result, we do not require additional hardware to track the current position and head orientation. Furthermore, independent of the current position and head orientation, we can simultaneously visualize all locations of the parts to be picked for the current shelving unit, allowing the user to optimize his movements. While these advantages do not imply that our system is superior, it at least justifies investigations, especially as our solution’s goals are to be less costly and more flexible.

Similar to our solution with the graphical pick chart, industry has developed a new solution using graphical representations of the shelves on mobile scanning devices [73].

4.2 Visual-Based Picking Supported by Context Awareness

In the work of Iben et al. [27], we evaluated a HMD system aided by context feedback (see Figure 2) and compared it to a text-based paper picklist with a between-subjects study design (see Figure 3). HMD users made noticeably fewer mistakes where context awareness could be applied, and the total number of errors trended towards fewer errors. Picking speed of HMD users was also faster. However, these results were expected due to an optimized ordering, reducing the required travel distances. Therefore, a more controlled experiment was required to show the benefits of one system over the other.

4.2.1 Improving the Experimental Procedure

The different ordering between the paper pick lists and the HMD solution resulted from the fact that the paper-based pick lists reproduced the ordering that was used at an actual picking setup in industry while the HMD solution used an ordering that optimized the required traveling. For better comparability, it would have been necessary to use the same ordering for both methods. In following studies we have therefore always tried to design the study in such a way that the reasons



(a) Context from a correct pick



(b) Context from a wrong pick

Figure 2: Visualization of Picking and Context information



(a) HMD picking setup

Bodenplatte	Wand links
R103A 11 x 1	R103A 22 x 1
Dach links	rot
R103C 11 x 1	R103A 31 x 1
schwarz	R103B 13 x 2
R103C 32 x 1	R103B 31 x 1
R103D 11 x 1	R103C 21 x 1
schwarz	Wand rechts
R103D 11 x 2	R103A 22 x 1
braun	rot
Dach rechts	R103A 32 x 1
R103C 11 x 1	R103B 11 x 2
blau	R103B 31 x 1
R103C 31 x 1	R103C 21 x 1
R103D 12 x 1	
Huette	
R103C 12 x 1	
R103D 32 x 1	
gruen	
Tuer	
R103A 12 x 1	
schwarz	
R103C 12 x 1	
R103D 22 x 1	
gelb	

(b) Paper pick list

Figure 3: Compared Methods

for differences are more easily determined.

We evaluated a picking zone in industry where workers are required to accomplish assembly steps during the picking process. To preserve validity with the tasks performed there, we required assembly steps in the initial study during the picking process. Nevertheless, as the assembly steps require a certain amount of time, evaluating differences in picking speed becomes more difficult (meaningful and statistically significant results regarding picking speed differences require more participants). Consequently, for the following studies we removed the assembly steps.

In a previous pilot study and also in this study, we observed some issues with the Trivisio M3 color see-through HMD. Participants required significant time to become accustomed to wearing the Trivisio M3 color see-through HMD. To have a manageable experiment duration and to avoid an ordering effect, we choose a between-subjects study design with a duration of two hours. After the studies we observed that a Micro Optical SV-6 HMD showed fewer issues and that users accommodate to this HMD much faster. For the following studies we switched to a Micro Optical SV-6 HMD and were able to choose a within-subject study design⁴ (which was more sensitive to conditions).

⁴In the following studies the subjects used different orders of the conditions (determined by a balanced Latin square design) to avoid an ordering effect.

Chapter V

COMPARING FOUR PICKING METHODS

© ACM, 2010. This is a minor revision of the work published in “An empirical task analysis of warehouse order picking using head-mounted displays,” by WEAVER, K. A., BAUMANN, H., STARNER, T., IBEN, H., and LAWOW, M. in *CHI '10: Proceedings of the 28th international conference on Human factors in computing systems*, pp. 1695–1704, <http://doi.acm.org/10.1145/1753326.1753580>. [77]

5.1 Introduction

In the work of Iben et al. [27] we compared a text-based paper pick list to a text pick list rendered on a HMD. Context sensing was shown to reduce pick errors where context awareness could be applied. However, the main improvement of the wearable solution was attributed to the optimized sorting which reduced the required travel distances. While attempting to replicate reasonable scenarios in industry, the experimental design had some confounds that potentially limited the quantitative effects that could be attributed to the interfaces.

We created an experimental design better suited to isolate the variables involved in order picking while still maintaining reasonable similarity to order picking environments we (and others) have observed in industry. To reach a higher picking performance we designed a new graphical representation increasing the picker’s time of item identification. We compared this graphical representation on a HMD to a paper-based solution using the same graphical representation, a paper-based text list, and a pick-by-voice system.¹

¹We first wanted to see how the graphical representation performed without any additional context feedback and thus in difference to the previous study we deliberately did not use context feedback.



Figure 4: Arrangement of parts and shelves. Two sets of shelves, A and B, each contains 4 rows of 3 part bins.

5.2 Experimental Design

This section describes the layout for the warehouse used in the study as well as a general definition of the pick task. The four picking methods are described in detail.

5.2.1 Warehouse Layout and Task Description

The study took place at the shop floor of BIBA² (see Figure 4). The layout consisted of two shelving units (A and B). Each unit had four rows and each row housed three part bins. Each part bin was represented with a two digit number. The first digit indicated the row of the part bin with 1 being the top row and 4 being the bottom row. The second digit indicated the position in that particular row with 1 indicating the left side, 2 indicating the middle and 3 indicating the right side of the row. A part with the number 31 would be in the third row from the top and on the left side.

A task required picking the parts for three orders at the same time. A pick is defined as reaching into a part bin and removing one or more parts from the bin. A place is defined as putting all of the items currently being carried into an

²<http://www.biba.uni-bremen.de>



Figure 5: Parts in the three order bins from a completed task.

order bin. An order was generated by randomly selecting four parts bins from a shelving unit.³ One part each was picked from three of those part bins, and the fourth bin required a pick of two of the same parts. Four picks were chosen because four independent items plus or minus one is the number of unconnected things that a person can keep in short term memory simultaneously [17]. A person can reasonably remember all four picks by receiving the information once and then picking all of the parts from the shelf. The process of randomly selecting part bins was repeated for both shelves which resulted in a completed order being ten total parts. Each task required five parts from each shelf for each order. Figure 5 shows the parts collected for all three orders in a task. The parts were small enough so that the participants could hold all of the parts for a single order in their hands so that only one place per order was necessary at each shelf. Two shelving units were employed instead of one in order to add complexity to the task and try to induce the participants to make errors. The next section will describe how the participants completed a task with each of the four picking methods tested in the study.

³By always choosing four picks per shelf per order we can assume that the complexity of all tasks is very similar, which allows us a direct comparison of the tasks duration without an additional normalization.

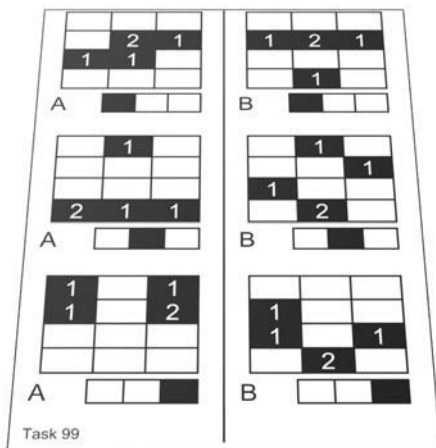
A	
1	22 x 2
	23
	31
	32
2	12
	41 x 2
	42
	43
3	11
	13
	21
	23 x 2
B	
1	21
	22 x 2
	23
	42
2	12
	23
	31
	42 x 2
3	21
	31
	33
	42 x 2

Task 99

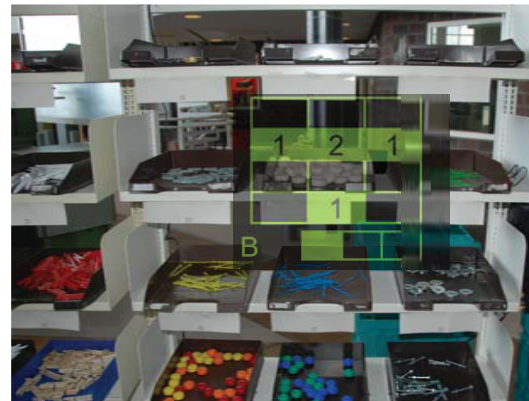
(a) Paper (text)



(b) Audio



(c) Paper (graphical)



(d) HMD

Figure 6: The four picking methods. The same task is displayed with each method. The audio and HMD versions only show what is accessible to the picker while filling part of order 1 on shelf B.

5.2.2 Picking Methods

Figure 6 shows the four picking methods tested in the study. Each image shows how information would be presented for the same task for easier comparison between the four picking methods. The completed result of the task represented in Figure 6 is depicted by the order bins in Figure 5.

5.2.2.1 Text-Based Paper Picking

The text-based paper picking method can be seen in Figure 6a. Using this method, participants were asked to retrieve a piece of paper from a plastic bin which contained a list of all the parts needed for a single task. Parts were first separated by

shelf (A or B) and then by order number (1, 2 or 3). Within an order section was a list of four part numbers. Parts needed to be picked twice were indicated with a “x 2” after the part number. Each order section was separated by a horizontal line. After completing the task, participants handed the completed order and parts list to the experimenter.

5.2.2.2 Audio Picking

In this method, participants wore a backpack containing a Sony Vaio UX ultra mobile computer. The computer was connected to headphones which provided the picking instructions. A Wizard of Oz approach was used for speech recognition. A human wizard listened for voice commands and initiated the appropriate computer response. Information was provided in a list manner much like that in the text-based paper method. In order to get the next line of instruction, participants were asked to say “okay.” Upon starting a task, participants were told “Regal A (shelf A).” The system then went through the list of parts for shelf A order 1 individually. For the part that was picked twice, the participant was told the bin number followed by “mal zwei (times two).” Once all of the parts were picked for order 1, the participant was told “fertig eins (completed 1).” Upon completing the last order for shelf A, the participant was told “fertig 3; Regal B (completed 3; shelf B).” The audio method was literally a spoken copy of the text-based paper picking method with the exception that in the audio version the order number was given just prior to placement in the bin instead of at the beginning of the picking. Participants were also allowed to repeat a command if they were unable to hear it by saying “noch mal (repeat)” or to step back to the previous command by saying “zurück (back).” In addition, participants were instructed that they could say “okay” in advance and in quick succession to avoid delays in picking. The audio picking method can be seen in Figure 6b. The instructions shown are for a single part on shelf B in order 1.

5.2.2.3 *Graphical Paper Picking*

The graphical paper picking method did not rely on part bin numbers to indicate the desired parts in a task. Instead, a grid consisting of 3 columns and 4 rows was displayed to represent the layout of the shelf. The bins to pick from were represented by black cells with a number inside indicating the number of parts to grab from that particular bin. Below the grid was a single row with three columns to represent the layout of the order bins. Again the black cell indicated the relevant order bin. This representation resulted in 6 images one for each order on each shelf for a single task. These images were arranged on a single piece of paper as seen in Figure 6c. The graphical representations for shelf A were in one column along the left side and the graphical representations for shelf B were along the right side of the paper.

5.2.2.4 *HMD Picking*

In this method, participants wore a backpack containing a Sony Vaio UX series ultra mobile computer. A monocular HMD device (MicroOptical SV-6) placed over the picker's dominant eye was connected to the computer to provide the visual instructions. The HMD system repeated the representation of the graphical paper method but instead of showing all of the images for a task at the same time, participants were shown a single image for a single order on one shelf. To provide better perceptibility on the HMD, black was used as the background color (instead of white) and yellow as the foreground color (instead of black). Figure 6d shows the participant's view for order 1 on shelf B. In order to see the next image, participants said "okay." If the participant wished to go back in the task in order to correct mistakes and see previous images, they can say "zurück (back)." Although the focus of the experiment is this final HMD picking method, it was important to include both graphical representations methods in the experiment to determine if any advantages found in the new HMD picking method were due to the graphical nature of the representation alone or due to other factors unique to the HMD.

5.2.3 Environment

Figure 7 shows the general setup. Two video cameras were used to record the experiments. One camera faced the back of the shelves to capture the participant picking items from the part bins. The second camera looked along the shelves so that it had a view of the participant placing items into the order bins. Two monitors were used, one facing each camera. The monitors always displayed a running clock so that the videos for the two cameras could be synchronized with each other and with the logs from the computers in the experiment. The monitors displayed most of the information which was being saved into the logs during the course of the experiment to aid in synchronizing the video feed and the raw data in post-study analysis. In the case of the audio method, the monitor displayed text versions of what the participant was hearing as well as interactions from the user. For the HMD method, the monitors showed the participant's current view in the HMD. For all four interaction methods, the monitors would show when the participant had placed parts in the order bins based on the wizard's input. In Figure 7, the *Camera 1 Monitor* shows that the participant is working on task 93. He has just finished placing objects in order bin number 2. The *Paper List Bin* is where the participant retrieved the paper task forms for the text-based paper and graphical paper picking methods.

Two researchers were required for this study. The wizard in the lower left corner of Figure 7 presses buttons on the tablet PC (a teXXmo Kaleo GX) to indicate when the participant has begun the task, placed objects in an order bin, or finished the task. For the audio and HMD methods, the *Wizard* is also responsible for responding to verbal commands from the participant to initiate the proper response from the computer system. The second researcher is stationed in the *Part sorting* area in the upper left hand corner of Figure 7. This person is responsible for taking pictures of the *Camera 2 Monitor* at the beginning of each task so that photographic data can be connected to its relevant task. Upon the completion of a task, this person retrieves the filled order bin and takes a

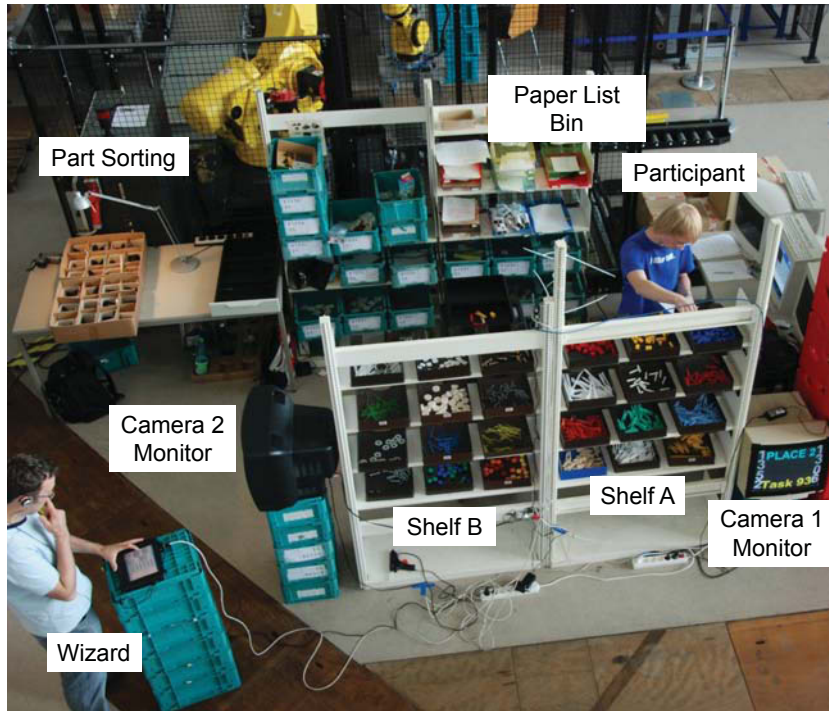


Figure 7: View of people, parts, and equipment in the experimental setup

picture of the parts inside for accuracy analysis. Parts were then sorted into their appropriate compartments in two trays for easy return to the part bins. The second researcher refilled the part bins between each method while the wizard debriefed the participant on the previous method and helped prepare them for the next method.

5.2.4 Method

Twelve participants (eight male, four female) were recruited for the study from the University of Bremen. Ten participants were right-handed and two participants were left-handed. All participants were tested for eye dominance to determine placement of the HMD which only covered one eye. The participants held their thumbs out at arms length and closed one eye. If the position of the thumb moved relative to the background, then the closed eye is dominant. Ten participants were right-eye dominant, one participant was left-eye dominant, and one participant was uncertain but used the left eye for the purposes of the study. This proportion of right-eye to left-eye dominant participants is consistent with that of the general population [19]. While it is not certain that eye dominance will impact

Die Aufgabe war leicht zu erlernen. <i>The task was easy to learn.</i>
Die Aufgabe war unangenehm auszuüben. <i>The task was uncomfortable to perform.</i>
Ich konnte die Aufgabe schnell ausüben. <i>I could perform the task quickly.</i>
Ich machte Fehler beim ausüben der Aufgabe. <i>I made mistakes while performing the task.</i>

Table 1: List of Likert scale statements.

performance, some studies show there is potential impact [51]. All subjects were native German speakers. Although everything is described in English here, all instructions, interactions with the picking methods, and survey instruments were provided to the participants in German during the study.

Due to the participants’ unfamiliarity with the four picking techniques to be tested and with warehouse picking in general, participants first completed a training phase. During the training phase, the experimenters explained each method in turn and allowed the participant to perform five tasks (involving a total of 120 picks) using each of the methods. The order of presentation of the four picking methods during the training phase was text-based paper, graphical paper, audio, and finally HMD. After completing the training sessions, the participants then began the testing session of the study. During the testing phase, the order the participant used each picking method was determined by a balanced Latin square design. The balanced Latin square design created four unique orders of presentation. By using twelve participants, we ensured that each order was used by three participants in the testing session and thus reduced ordering effects in the data. All statistics provided in this paper are derived solely from the order-counterbalanced testing phase. Participants performed ten pick tasks with each picking method during the testing session and data from the last eight tasks for each of the four picking methods was used for analysis. Times were recorded for each interaction with the interface in the case of the HMD and audio picking versions as well as the start and end times of a task. After using each picking method, participants

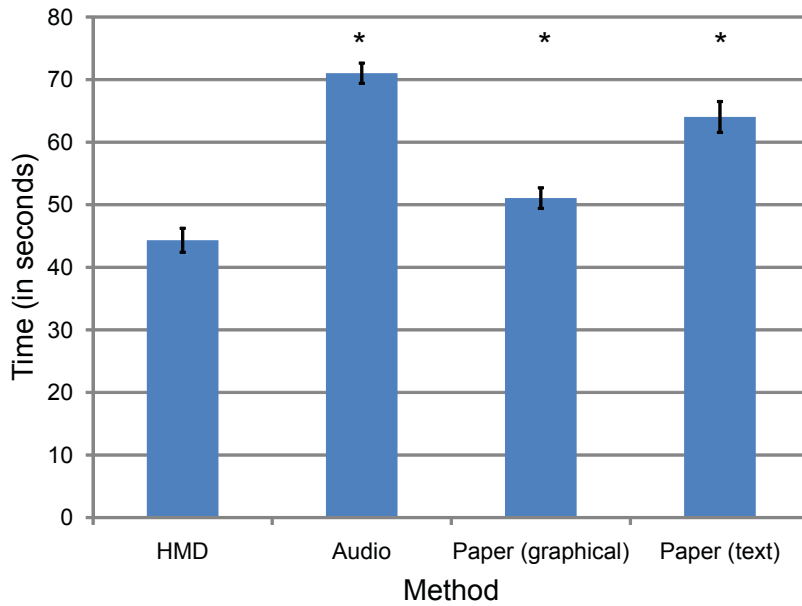


Figure 8: Time per task. A * indicates a significantly slower time than the HMD.

were asked to complete a NASA-TLX survey and to rate the learnability, comfort, speed, and accuracy of the method on a seven-point Likert scale (shown in Table 1). At the conclusion of the testing phase, participants were asked to rank the methods from best (1) to worst (4) based on overall preference, learnability, comfort, speed and accuracy (see Appendix C for the complete questionnaire). Accuracy data was also collected from photographs of the order bin after each task.

5.3 Results

We designed the experiment with the paradigm of evaluating one new picking system (in this case the HMD-based system) in comparison with other methods. The HMD was evaluated against the two paper-based picking methods and the audio picking method using both performance and usability measures.

5.3.1 Performance Measures

5.3.1.1 Task Times

To achieve accurate task times, the start and end times extracted from the log files were verified and corrected by a self-written video annotation tool. For the paper-based picking methods, start time was defined as when the participant picked up the paper task form. The start time for the audio picking method was defined as when the first instruction to pick a part was played. For the HMD-based picking method, the start time was defined as when the first shelf-order combination was displayed. For all methods, the end time was determined by when the last item was placed into the order bin. The average time per task for each of the picking methods can be seen in Figure 8. The error bars represent the standard error of the mean. A one-tailed paired samples t-test with Bonferroni correction for multiple comparisons was used to compare the average task time for each of the picking methods. The average time per task when using the HMD ($M = 44.33, SD = 6.63$) was significantly faster than the average time per task when using any of the other three methods: the graphical paper version ($M = 51.07, SD = 5.68$), $t(11) = 7.24, p < 0.05$ (one-tailed), the text-based paper version ($M = 64.03, SD = 8.53$), $t(11) = 24.40, p < 0.05$ (one-tailed), and the audio version ($M = 71.03, SD = 5.59$), $t(11) = 14.43, p < 0.05$ (one-tailed).

Figure 9 shows the average time required for participants to complete the last eight tasks in the testing session for each of the four picking methods. Each of the lines is relatively straight indicating that by the last eight tasks the participant had reached a consistent performance level in each condition. Learning effects seem minimized.

5.3.1.2 Accuracy

Pictures were taken of the order bins after each task to evaluate per task accuracy based on number of substitutions, insertions, and deletions. Substitutions are when one part was swapped for another part, insertions are when an unrequested

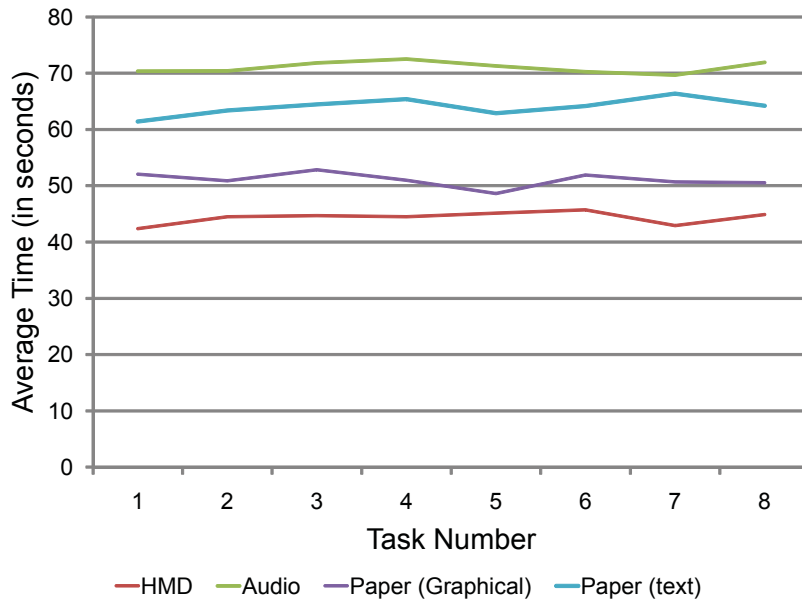


Figure 9: Comparison of the average time to complete each task per method

part was put in an order bin and all other requested parts were correctly picked, and deletions are when a part was forgotten and not replaced by another object. When an error was detected, it was confirmed through review of the video from the pick. This analysis helped determine the cause of an error. One common error was placing the items from an order into the wrong order bin. In the graphical picking methods, participants sometimes started picking from the wrong part bin and thus all of the subsequent picks were misaligned as well. In the audio picking method one participant would place parts from order 2 into the order 3 bin in shelf B and then skip order 3 completely. In some cases participants only picked one part instead of two from the bin where duplicates were required.

The total number of substitutions, insertions, and deletions in a task was combined to create a per task error value. A one-tailed paired samples t-test with a Bonferroni correction was used to compare participant’s average per task accuracy based on substitutions, insertions, deletions and errors for all 4 picking methods. The HMD ($M = 0.010, SD = 0.036$) resulted in significantly fewer insertions than the text-based paper method ($M = 0.094, SD = 0.108$), $t(11) = -2.60, p < 0.05$

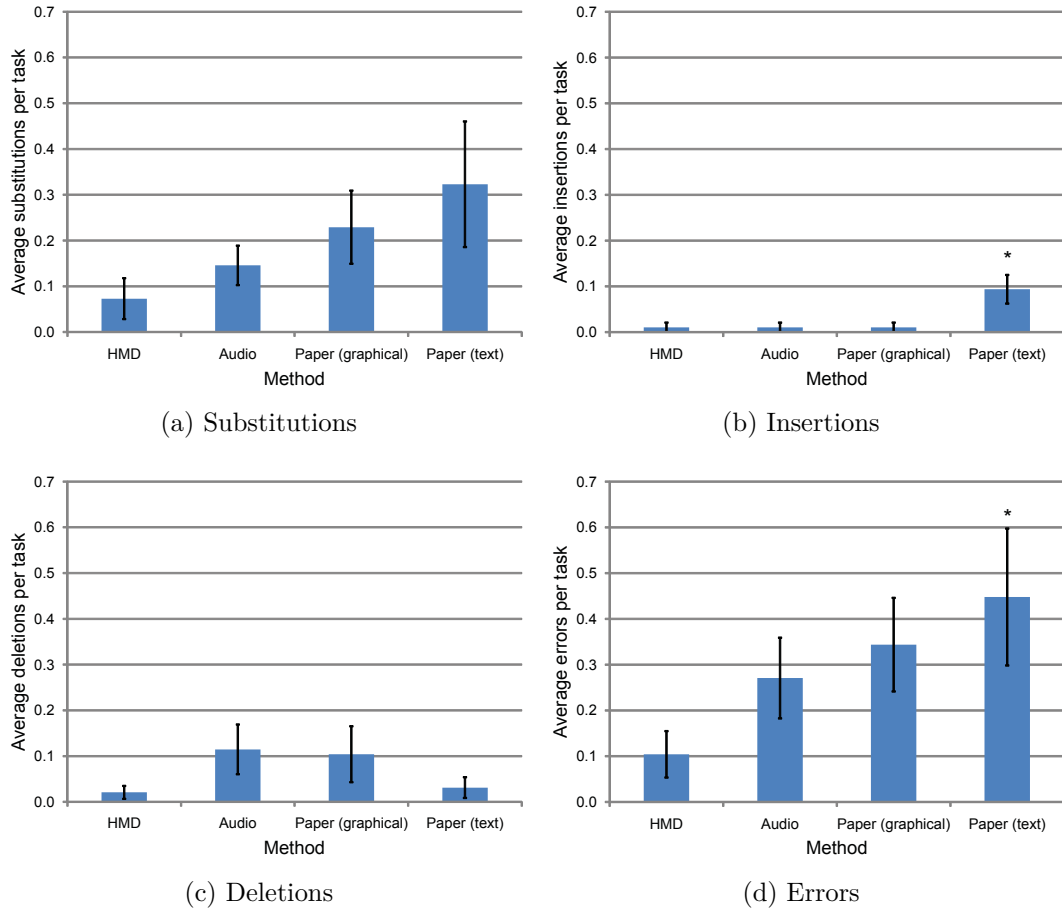


Figure 10: Picking accuracy. A * represents a significantly higher number of errors than the HMD.

(one-tailed). With regards to overall errors, (the sum of all insertions, deletions and substitutions) the HMD ($M = 0.104, SD = 0.175$) resulted in significantly fewer errors than the text-based paper method ($M = 0.448, SD = 0.518$), $t(11) = -2.45, p < 0.05$ (one-tailed). Figure 10 shows the comparison between substitutions, insertions, deletions and total errors across each of the four picking members. The error bars show the standard error of the mean. Based on Figure 10c, it appears that the text-based paper version also performs pretty well in reducing errors due to deletions.

5.3.2 Usability Measures

5.3.2.1 Post-Study Rankings

The median post-study ranks for overall preference, learnability, comfort, speed, and accuracy for all four picking methods is shown in Table 2. The ranks were

Measures	Picking Method			
	HMD	Audio	Paper (graphical)	Paper (text)
Overall	1.0	2.0 *	2.5 *	4.0 *
Learnability	2.5	2.5	2.0	4.0
Comfort	1.0	2.0	3.0	4.0 *
Speed	1.0	3.0 *	2.0 *	4.0 *
Accuracy	2.0	2.0	3.0	4.0 *

Table 2: Post-study rankings. A * indicates a significantly worse rank than the HMD.

compared using a Wilcoxon Signed Rank Test, the non-parametric equivalent of a paired samples t-test, with a Bonferroni correction for multiple comparisons. Overall the HMD was ranked significantly higher than the other three order picking methods: audio, $z = -2.44, p < 0.05$ (one-tailed), with a large effect size ($r = 0.50$), graphical paper, $z = -2.86, p < 0.05$ (one-tailed), with a large effect size ($r = 0.58$), and text-based paper, $z = -3.21, p < 0.05$ (one-tailed), with a large effect size ($r = 0.66$). The HMD ($Md = 1.0$) was ranked again significantly higher than the text-based paper version ($Md = 4.0$) with regards to comfort, $z = -2.92, p < 0.05$ (one-tailed), with a large effect size ($r = 0.60$). On the speed measure, the HMD method was ranked significantly higher than audio, $z = -2.39, p < 0.05$ (one-tailed), with a medium effect size ($r = 0.49$), graphical paper, $z = -3.28, p < 0.05$ (one-tailed), with a large effect size ($r = 0.67$), and text-based paper, $z = -3.15, p < 0.05$ (one-tailed), with a large effect size ($r = 0.64$). When asked to rank each of the methods in order of resulting accuracy, the participants ranked the HMD ($Md = 2.0$) better than the text-based paper version ($Md = 4.0$), $z = -2.93, p < 0.05$ (one-tailed), with a large effect size ($r = 0.63$).

5.3.2.2 Picking Method Likert Scale Responses

Two of the Likert scale statements were positively worded and two of the statements were negatively worded. For the statistical tests in this paper, we flipped the responses for the negatively worded statements so that 1 is always the worst and 7

Measures	Picking Method			
	HMD	Audio	Paper (graphical)	Paper (text)
Learnability	7.0	7.0	7.0	6.0 *
Comfort	6.0	5.0	5.0	4.0
Speed	6.0	6.0	6.0	5.0 *
Accuracy	4.5	5.5	4.0	3.0 *

Table 3: Likert scale responses. A * indicates a significantly lower (worse) score than the HMD.

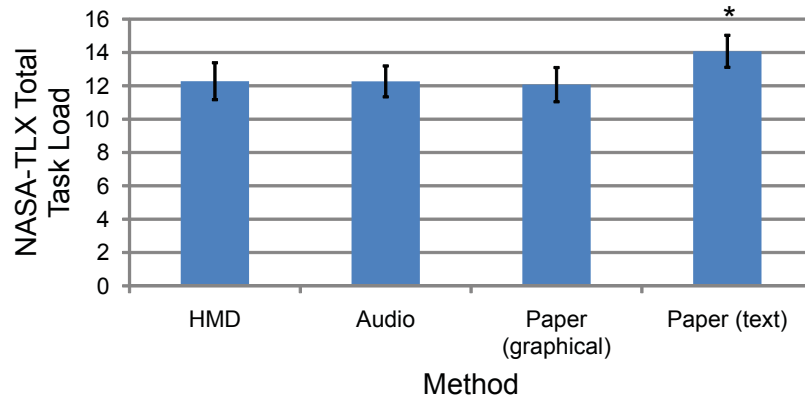


Figure 11: Overall task load

is always the best. A one-tailed Wilcoxon Signed Rank Test was used with a Bonferroni correction. The HMD received a significantly higher score ($Md = 7.0$) than the paper text version ($Md = 6$) with regards to learnability, $z = -2.16, p < 0.05$ (one-tailed), with a medium effect size ($r = 0.44$). The HMD ($Md = 6.0$) was also given a better score for speed than the text-based paper version ($Md = 5.0$), $z = -2.70, p < 0.05$ (one-tailed), with a large effect size ($r = 0.55$). On the accuracy measure, the HMD ($Md = 4.5$) was also given a better score than the text-based paper version ($Md = 3.0$), $z = -2.3, p < 0.05$ (one-tailed), with a medium effect size ($r = 0.46$). The median scores reported by the users for all parameters and all picking methods are shown in Table 3.

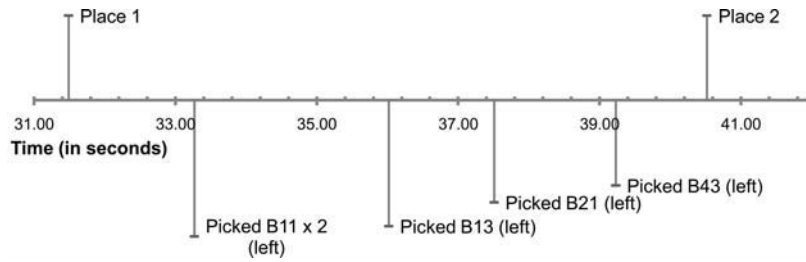
5.3.2.3 NASA-TLX

The NASA Task Load Index Survey (NASA-TLX) was administered after each picking method's testing phase. A one-tailed paired samples t-test with a Bonferroni correction for multiple comparisons was used to compare the overall task load for each method and each of the task load sub-scales. The total task load when using the HMD ($M = 12.3, SD = 3.8$) was significantly lower than the total task load when using the text-based paper version ($M = 14.1, SD = 3.3$), $t(11) = 4.27, p < 0.05$ (one-tailed). The HMD did not show a significant improvement over the graphical paper method or the audio method with regards to the total task load. None of the other comparisons achieved significance. Figure 11 shows a graph comparing the overall task load.

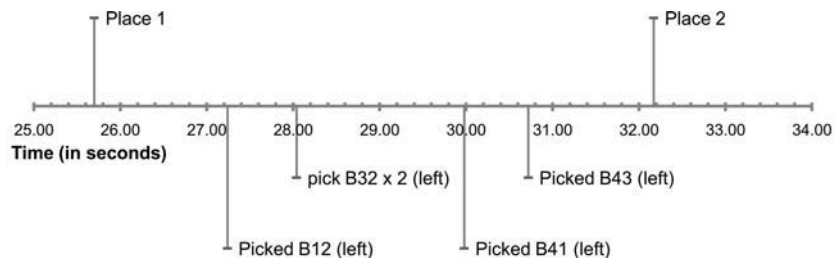
5.3.3 Timelines

The data from a participant who was comparatively fast for all of the picking methods was selected for an analysis of picking strategies. Figure 12 shows detailed timelines of all of the picks, placements and interactions for each modality for the first order from shelf B on one of the tasks. Figures 12a and 12b, which show that the timelines for text-based paper and graphical paper, are highly similar. The participant only picks objects with his left hand. The paper task lists are being held with the right hand. The text-based paper timeline (Figure 12a) shows that the objects were being picked at a fairly even rate indicating that it takes approximately the same amount of time to interpret the instructions and move to the next picking location. The graphical paper timeline (Figure 12b) shows a more punctuated picking rate. The first two objects are picked, and then the second two. The participant may have used the graphical nature of the presentation to remember the first two picks because they were in the same column and then the second two picks because they were both in the same row, allowing for faster picking.

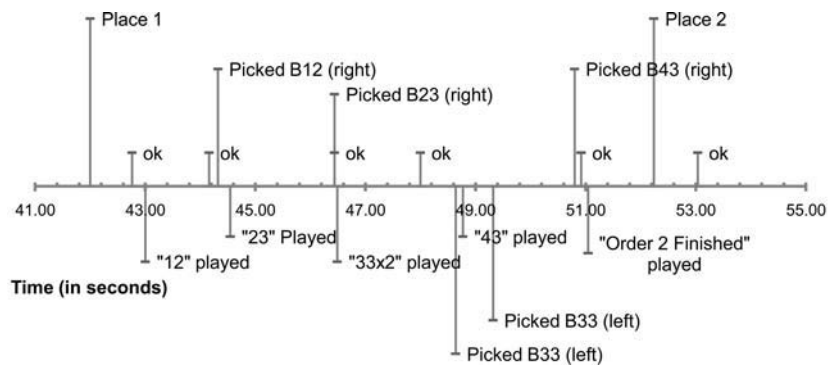
The audio and HMD picking methods allowed for hands-free interaction with



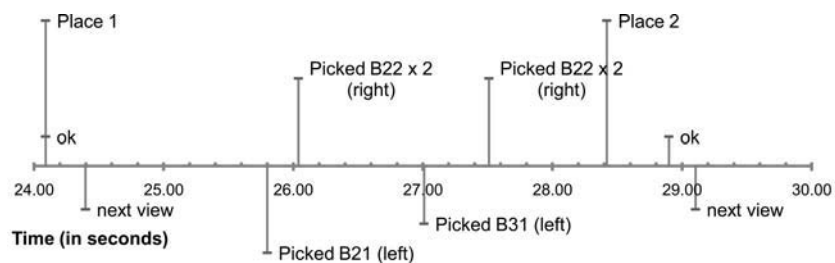
(a) Paper (text) timeline



(b) Paper (graphical) timeline



(c) Audio timeline



(d) HMD timeline

Figure 12: Timelines for each of the four picking methods

the order data. Correspondingly, participants used both hands for picking. Figure 12c shows the timeline for the audio picking method. The timings for picking from the part bins and placing in the order bins are shown, as well as the voice commands from the participant and instructions from the audio device. The first thing that can be noticed is that participants do indeed use both their right and left hands with the audio picking method even though instructions are only being provided serially. The serial presentation of picking information is one disadvantage of an audio presentation of order information in a densely packed warehouse environment. If the participant needed to travel farther to the next picking location, there would be sufficient time to receive the instructions before the part bin is reached. This participant did use some optimizations to pick more quickly. The “okay” command was given slightly before the instruction for part B12 so that the next instruction could begin. The gap between “okay” command and pick was even larger after the instruction to pick part B33 twice. Unfortunately, in this case the participant was not as attentive to the quantity of the first command. The participant started by picking one object from bin 33 and then realized that two parts were required and had to quickly reach into the part bin again. There was also considerable delay between placing parts in the order bin and giving the command for the next instruction after order 1 and order 2.

Figure 12d shows the HMD timeline. Here the participant actually says “okay” at the same time that parts are being placed in the order 1 bin. The participant is also alternating picking with right and left hand. As with the graphical paper picking method (Figure 12b), the participant is picking with a more punctuated rate: picking both objects from row 2 first, and then picking the two objects in column 1. The combination of being able to use both hands and always having the display visible may make picking faster than any of the other picking methods.

5.4 Discussion

The HMD performed considerably better than the traditional method of text-based paper for many measures. In this study, we showed that the HMD resulted in significantly faster picking times not only over the text-based paper version, but also over the graphical paper and audio versions. Because the HMD was faster than the graphical paper version, we can see that it is not just the graphical presentation of the information in the HMD that results in faster picking. Another clear advantage for the HMD was that it allowed the pickers to use two hands to collect parts (Figure 13). When using the graphical paper version, only one hand could be used because the other hand was holding the paper. Some participants suspended the paper from the shelves while picking, but these participants also made many mistakes. The HMD display was also adjusted so that the part bins and the display were at the same focal distance, which meant that unlike the two paper versions, in the HMD method participants could maintain constant focus.

The audio version was the slowest picking method. Our warehouse layout was not the best for testing the desirability of an audio interface in warehouse picking. If the parts had been distributed among multiple banks of shelves, the audio method would have had less of a disadvantage. Participants also had more opportunities to optimize their picking with the audio method, but did not take advantage of them. Participants could have requested information for the next part while in motion for the current part, but instead most waited until after the current part had been picked. There may be a confound over the possible processing delay in the audio interface due to the reaction time of the wizard with regards to the results in this study. The average time from user request to computer action in the audio method was 0.4 seconds. Processing time, while currently unknown, would also be required for speech recognition systems to interpret the commands. Because the participants did not take advantage of all of the optimization possibilities when using the audio picking method, and the fact that the total duration



Figure 13: A participant uses two hands to collect parts while wearing a HMD.

of all audio prompts for a task without any delay between commands is 47 seconds, there was little chance for the audio version to outperform the HMD version in this study. A new study focusing on audio interfaces using the same experimental method described in this paper could be implemented in order to better understand the causes of delay with this picking method.

The participants in the study did not necessarily have previous experience with HMDs, which could have affected their response to the novel device. According to the two measures of usability we collected, ranking and Likert responses, the HMD was not significantly harder to learn than any of the other methods. In fact, participants reported that the text-based paper version was harder to learn.

There were no significant differences between the HMD and the three other picking methods for any of the sub-scales in the NASA-TLX survey, but the HMD did show significant improvement over the text-based paper version in overall task load. This improvement is consistent with expectations. The audio method and the text-based paper method are the only two methods that require the participant to pay attention to the labels on the part bins. The reduction in task load for the audio method and not for the text-based paper version is most likely due to the audio method's presentation of only one part at a time. In the text-based paper

version, the entire list of parts for the task is available simultaneously and the participant must keep track of what has already been picked.

The participants were fairly capable of evaluating their own performance when using the four picking methods. Participants felt that they were fastest using the HMD, and this method indeed proved fastest. The paper graphical method was predicted and shown to be the second fastest. The participants did feel like they were faster on the audio method than with the text-based paper method, when in fact the opposite was true. This conflict between perception and ground truth is a positive endorsement for the audio method because it indicates that participants did not feel like they were being slowed down while waiting for the audio instructions. Participants were also able to correctly evaluate their accuracy. Participants felt that their accuracy suffered more in the text-based paper version, and this was demonstrated in their actual accuracy scores. This consistency of user impressions and actual performance is important.

5.4.1 Evaluation of User Study Design

The study we created was sensitive to the differences in the four picking methods, more so than both Iben et al. [27] and Reif et al. [59] with regards to the time measure. The user study was less able to differentiate between the picking methods in terms of errors. One common error in warehouse picking is when the picker loses track of which shelf they are at, causing them to pick the parts from the wrong shelf. Some participants divided the parts they had picked from the shelves so that one shelf's parts were at the edge of the order bin closest to them and the parts from the other shelf were at the farthest part of the order bin, allowing them to keep track of which parts had been picked from which shelf and for which order. A possible modification to the experimental set up would be to provide smaller order bins which do not allow this division or to find new ways to make the task more difficult by incorporating more shelves.

The method of synchronizing the time with the computers for the picker, wizard, and for the display monitors was a success. This synchronization made it

very simple to evaluate the data at the end of the study. The time stamp information in the logs and on the video feed was invaluable for consulting the video to verify inconsistencies with the accuracy data. It was also very important to always ensure that there were at least 20 parts in each of the part bins. The participant never had to struggle to pick parts from a particular bin and this helped to guarantee that picking times during the beginning of a method's testing phase stayed consistent with the picking times at the end of the testing phase.

The user study was sufficient for discriminating between the four picking methods based on efficiency and usability factors. However, the social structure of the workplace and the interactions between other pickers in the environment play an important role as well [44]. It may be possible to extend the experimental environment described in this paper to incorporate multiple pickers and capture some of the effects of the social work environment. Other study designs would be necessary to investigate such factors as large scale deployment and effects of fatigue that may occur from long term use of a HMD. However, this experimental setup succeeds in allowing the interaction designer to accurately compare and discriminate among many task guidance systems simultaneously, something which may not be possible with a more ethnographic-centered or long-term study design.

One advantage of the experimental protocol in this study is that it provides the researchers with a wide range of performance and usability data for task guidance systems. The incorporation of video cameras to record the experimental session allows for easy recovery of experimental data in the case that the logging mechanism in the computers fails.

Chapter VI

USER-INTERFACE OPTIMIZATIONS

© ACM, 2010. This is a minor revision of the work published in “Evaluation of Graphical User-Interfaces for Order Picking Using Head-Mounted Displays,” by BAUMANN, H., STARNER, T., IBEN, H., LEWANDOWSKI, A., and ZSCHALER, P. in *ICMI '11: Proceedings of the 2011 international conference on Multimodal interfaces* pp. 377–384, <http://doi.acm.org/10.1145/2070481.2070553>. [9]

6.1 Introduction

The very promising results regarding the graphical pick chart in combination with a HMD in the previous study, led me to pursue this solution. A logical next step would have been to test our HMD system in a real picking environment of our automotive project partner, comparing it to a pick-by-light system and determining its suitability in an industrial environment. However, as errors can stop an assembly line, creating large losses, I first wished to optimize the system to decrease the error rate based on observations from our previous studies. I pursued extensions suggested by subjects and interaction principles in the literature. After developing many interface variants (see Figure 18 for some examples) it was unclear if they would improve the system or if they might diminish the performance of the system. Some variants were mutually exclusive. Thus, the goal of the study I present in this chapter is to identify extensions and user interface variations which suit the subsequent industrial study discussed in Chapter 7. To avoid multiple hypothesis statistical testing issues inherent in testing all combinations of the extensions, we have focused our attention on two hypotheses:

Color The use of colors that match the rows of the shelves with the rows of the HMD pick chart will reduce errors (as color is perceived easily and helps the

picker to identify the correct row).

Context Highlighting detected picks (both correct and incorrect) in the HMD pick chart will reduce errors.

6.2 Color Experiment

The goal of this experiment was to test the color hypothesis and gain an intuition on the amount of improvement that might be expected. Monochrome HMDs are often brighter, lighter, less bulky, less expensive, and/or use less power than color HMDs. Thus, if the improvement with color is negligible, we would feel free to specify monochrome equipment for industrial settings. In addition, we wanted to explore several variations of the interface to see if there were positive or negative trends in accuracy, workload, or picking speed that suggest the need for future experimentation.

6.2.1 Picking Environment

We constructed three shelving units in a laboratory of TZI. Each row housed three part bins, and each shelving unit had five rows (see Figure 14). The participants wore a vest made by teXXmo with a TX-1000 Wearable PC using a 1.6GHz Intel Atom Z530 and 1GB of RAM. An opaque monocular HMD device (MicroOptical SV-6) provided visual instructions. The HMD connected to safety glasses and was worn over the picker's right eye¹ (see Figure 15). The participants use a rugged mouse from Vuzix with two large buttons to navigate through the tasks. The mouse was carried vertically near the left hip.

¹An explanation why we decided to use the right eye can be found in Section 8.4.4.

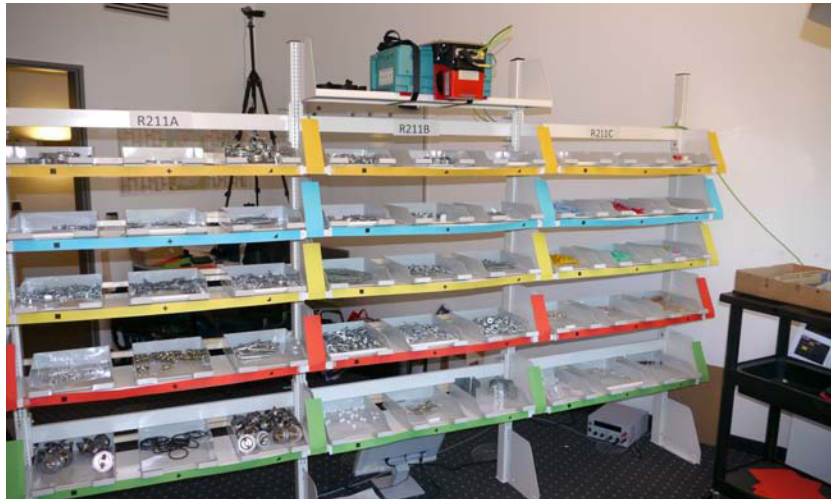


Figure 14: Three shelving units



Figure 15: Wearable and HMD



Figure 16: Order bins



Figure 17: Part bins (colored modalites)

6.2.2 Task Description

As in our previous study (see Chapter 5), the pick task consisted of picking the required parts for three orders at the same time. This process mimics what we observed as common in industrial environments. The participants used a pick cart with three order bins called *LINKS* (left), *MITTE* (center) and *RECHTS* (right) (see Figure 16).

A pick task starts by scanning a bar code with a bar code scanner. The first screen of the task is displayed in the HMD showing the first parts to pick. Each screen shows a pick chart of the parts to pick from one shelving unit for one order (see Figure 18a as an example). Every part bin in the pick chart is represented as a rectangle, and the size and position of this rectangle correlates with the size and position of the real part bin in the shelf. Part bins scheduled for picking are highlighted in the pick chart, and the number in the center of that rectangle defines the number of items to pick from it. The shelving unit identifier is shown on top of the pick chart; the order bin in which to place the picked parts is shown on the top right side of the screen.

Using Figure 18a as an example, the participant should make two picks from shelf R211B – taking three items per pick – and put them into the left order bin. After the first screen is completed the participant presses the lower mouse-button (*forward-button*) to see the next pick screen. The participant can navigate through all the screens of the current pick task using the mouse-buttons. One task always

consists of three screens (one screen for each order bin²). After the third screen is completed and the participant presses the *forward-button*, the system confirms the completion of the task and waits for the participant to scan the next task. The number of part bins from which to pick within a screen varies from one to six. The number of items to pick from a bin ranges from one to five. The number of picks per task ranges from 7 to 13 (11.4 in average). The increased number of shelves and the increased variation in the pick tasks compared to the previous study is chosen to increase the chance for errors and to make the setup closer to a real picking environment.³

6.2.3 User Interface Variations

We want to compare the pick chart variations shown in Figure 18:

Monochrome (M) This variant is similar to the pick chart of our previous study.

Monochrome, Ids (MId) This variant adds identifiers to the lower right side of the part bins in the pick chart. The first digit of an identifier indicates the row of the part bin; the second digit indicates the position in that particular row. Whenever a monochrome modality is used, the identifiers are displayed under each part bin on the physical shelf, allowing participants to verify the correct bin.

Colored (C) Each row on the pick chart and on the physical shelves is marked with corresponding colors to help identifying the correct row for each pick.

Colored, Symbols (CS) Symbols are added to the part bins and on the pick chart to help identify the correct column for each pick. Whenever a colored modality was used these symbols were also shown under each part bin in the shelves (see

²With randomly chosen order / shelf assignments, one shelf might require no screens and another shelf might require more than just one screen for a task.

³In the previous study we observed that participants learned the repeated pattern of: Four items per screen and three screens (for every order) per shelf, allowing the participant to make unrealistic optimizations which would not be possible in a typical industrial environment. The required normalization that arose from the varying task complexity is described in Section 6.2.6.

Figure 17).

Colored, Symbols, Descriptions (CSD) Descriptions of the items are added to the right side of the pick chart.

Colored, Symbols, Images (CSI) Images of the items are added to the right side of the pick chart.

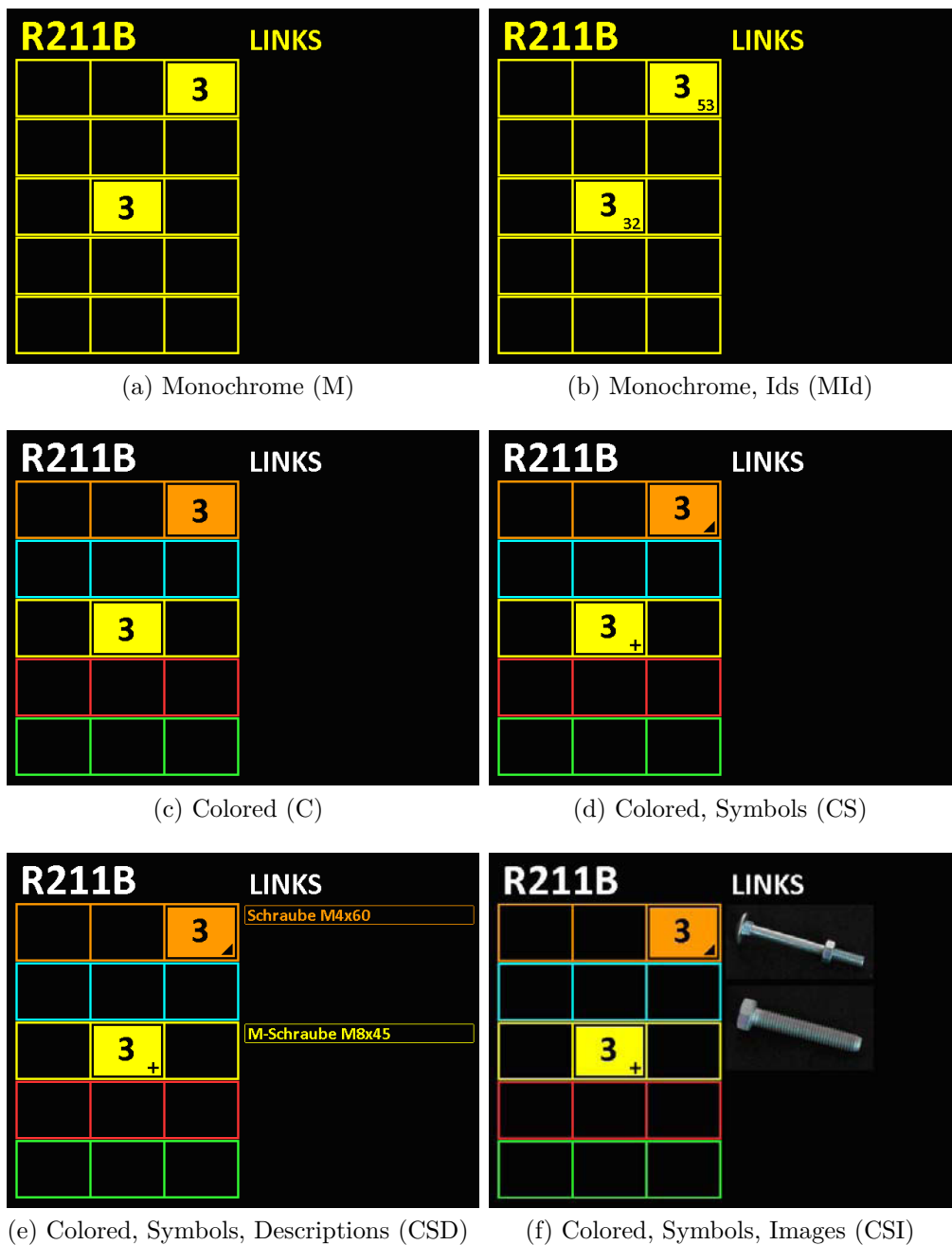


Figure 18: Modalities tested in the Color experiment

These conditions are grouped into three classes: the **Monochrome modalities (MM)** (Figures 18a and 18b), the **Colored modalities (CM)** (Figures 18c and 18d) and the **Colored modalities with descriptions or images (CM+)** (Figures 18e and 18f). Since our hypothesis concerns the effect of color on accuracy, our primary analysis will concentrate on the *MM* and *CM* classes. Post-hoc analysis on the additional classes will provide guidance for future experiments.

6.2.4 Method

Six participants were recruited; five were right-handed. All participants were right-eye dominant, and one participant wore glasses. Four subjects had some picking experience from previous employment in a logistics company. All subjects were native German speakers from the University of Bremen, and all instructions, interactions with the picking methods, and survey instruments were provided to the participants in German during the study. Participants were instructed to work as if they were in a real occupation and told that it was more important to avoid errors than to work extremely fast. The study took about two hours per participant, and participants were paid 20€.

All participants completed a training phase. During this phase, the experimenters explained each method in the order shown in Figure 18, and the participant performed two tasks using each method. The participants could pose questions to the experimenters, and the experimenters provided feedback in case of mistakes during the training phase. After completing the training sessions, the participants began the testing phase of the study. During the testing phase, the order in which the participant used each picking method was determined by a balanced Latin square design. Pick tasks were randomly generated in advance of the study, and the same sequence was used for each subject. Each participant performed seven tasks with each picking method during the testing session, resulting in 42 tasks (485 picks) for each participant.

Times were recorded for each interaction with the interface. The task time was defined as the time from the scan of the task to the last interaction through

the navigation buttons before the next pick task was read. After each modality the participant completed surveys containing subjective measures, including the NASA Task Load Index (TLX) [24]. At the end of the testing phase, participants were asked to rank the methods from best (1) to worst (6) based on overall preference, learnability, comfort, speed and accuracy. A free response space was provided as well (see Appendix D for the complete questionnaire). Picking accuracy was determined from pictures of the order bins after each task. Three cameras recorded the experiment from different views. When an error was detected in the pictures, it was confirmed through review of the video from the corresponding pick task. This analysis also helped to determine the cause of an error.

6.2.5 Accuracy

We use the following ontology when considering errors. **Errors** are composed of *Item mistakes* and *Wrong numbers*. **Item mistakes**, in turn, are divided into *Substitutions*, *Missing part* and *Additional part*. Finally, **Substitutions** are divided into *Wrong shelf*, *Wrong row*, and *Wrong column*. The classes which are not further divided are defined as follows:

Wrong number The participant picked from the correct part bin but took the wrong number of items. (The difference in number of items is not considered.)

Missing part; Additional part The participant missed a pick completely or picked from a part bin not requested. (Note that *Substitutions* take precedence where applicable. The number of items requested/picked was not taken into consideration.)

Wrong shelf; Wrong row; Wrong column The participant picked from the wrong shelf, row or column.

Figure 19 shows the mistakes in the *Color experiment*. One mistake within a modality (over all subjects) is equal to 0.0344% mistakes per pick.

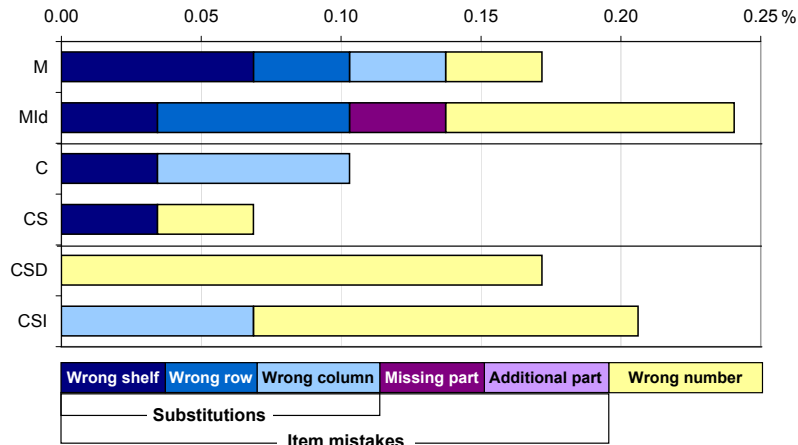


Figure 19: Mistakes/pick in Color experiment

As we formulated just one hypothesis per study, a correction for multiple comparisons is not needed for the hypothesis itself. There is a statistically significant difference between the average errors made in the monochrome (MM) conditions versus the color (CM) conditions (0.206% vs. 0.086% errors on average; $p = 0.0063$; one-tailed, paired t-test). Looking at the errors of the type *Wrong row*, on average there was one mistake of this type per 28 tasks for the MM conditions while there were no mistakes of this type made during the 168 pick tasks in the four colored conditions (CM and $CM+$). These findings support our hypothesis, which was that the use of color would improve accuracy.

6.2.5.1 Post-Hoc Analysis

We report p-values without correction for multiple comparisons (e.g., Bonferonni correction). Observations reported are intended as possible areas for future exploration.

The CS condition shows less errors than the M condition ($p = 0.038$) and the Mid condition ($p = 0.021$). The average number of errors is less than twice as low for the CM conditions than the $CM+$ conditions, which adds descriptions or images. Examining the errors in the $CM+$ conditions more carefully, we can see that more than 80% of the mistakes are of the type *Wrong number*. Considering only this type of mistake and comparing the CM conditions against the $CM+$

conditions, the *CM* conditions show only one error of this type (throughout the whole experiment) while there are 9 errors of this type for the *CM+* condition. A paired t-test for this comparison shows a p-value of 0.08 (two-tailed).

Examining the mistakes of the type *Item mistakes* within the *CM+* conditions, only two mistakes occurred in total, while within the *CM* conditions four mistakes occurred in total. Not a single mistake of the type *Wrong shelf* occurred in the *CM+* while in all other modalities at least one mistake of this type occurred. Although not significant, this effect might be caused by the additional information in the image, which helps the participants to recognize that they were picking from the wrong shelf. However, *CM+* conditions had more *Wrong number* mistakes. *Item mistakes* for *CM+* were the same or less than in the other conditions.

6.2.6 Speed

Comparing picking speeds between different modalities requires normalization of the recorded times. Each participant has an individual picking speed; in addition, the complexity of the tasks varies.

The first step in normalizing is to calculate the average picking time per task for each participant and then to divide each specific task's time by this average. This procedure results in normalized task times that allow comparing picking times for individual tasks between all participants.

In a second step, the normalized individual task times from step one are used to calculate the average normalized value for each individual task. The final normalization step divides the normalized values from step one by the corresponding normalized average task time. This second normalization allows the comparison of task times regardless of the individual task's complexity.

Comparing the normalized times of the *MM* and *CM* conditions, we get an average value of 0.988 (dimensionless value) for the *Monochrome modalities* and an average value of 0.987 for the *Colored modalities*. As these values are nearly the same, we think there is no relevant difference in speed between the *CM* and *MM* conditions.

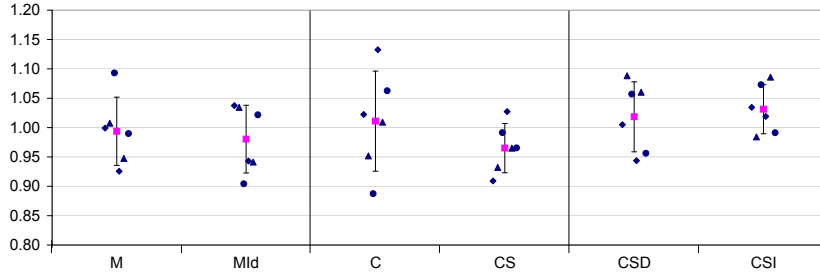


Figure 20: Pick speeds of the different conditions relative to the average (1.00); lower is faster

6.2.6.1 Post-Hoc Analysis

The fastest condition with a normalized average task time of 0.965 is *CS*. The slowest modality with an average of 1.031 is *CSI*, 6.9% slower than *CS*. A two-tailed paired t-test returns a p-value of $p = 0.028$. Also, the modality *CSD* is 5.6% slower than the modality *CS*. These modalities are probably slower because of the amount of time the worker refers to the additional information provided.

6.2.7 Subjective measures

We asked the participants to rank the six different conditions from first to last (6th) place. The median ranks are shown in Table 4. Comparing the rankings of the *CM* conditions against the *MM* conditions, all five categories show a p-value of $p < 0.05$ (using a Wilcoxon-Test with the hypothesis that the *CM* have a better ranking than the *MM*). Looking at the table, no single condition seems best. However, the two *CM* conditions stand out. Only in the category *Accuracy* does the *CSD* condition trend a little better.

	M	Mid	C	CS	CSD	CSI
Overall	6	4.5	2	2	4.5	3.5
Learnability	4.5	4	2	2	6	2.5
Comfort	6	4.5	2	2.5	4	2.5
Speed	5.5	4.5	1.5	2	4.5	2.5
Accuracy	5.5	5	3.5	2.5	2	2.5

Table 4: Ranking of conditions (lower values are better)

We also asked participants to rate their experience with the different conditions

as *very good*, *good*, *neutral*, *bad* or *very bad*. The participants gave only positive feedback on the *colored modalities* and rated the use of color for the row as *very good* (3 persons) or *good* (3 persons). The question *Did you like the use of images for the items to pick?* resulted in *neutral* (4 persons) or *good* (2 persons) responses. The inclusion of descriptions of the item was not as well received: *very bad* (2 persons), *bad* (1 person), *neutral* (1 person), and *good* (2 persons). The NASA TLX results did not show any significant difference between conditions.

During the open response section of the survey, participants judged the navigation as good. In particular, they liked the smooth navigation between screens. People with picking experience said that it required time to adapt to the new concept, but that they liked it. Many participants pointed out that additional information like the images helps to pick the correct part, but that the number of items to be picked seems to be less emphasized by the interface.

6.3 Context Experiment

In a preliminary study [27], we used a Wizard of Oz approach to display completed and inaccurate picks on a HMD. Adding this context information reduced mistakes as compared to a text-based paper pick list. However, the standard text-based pick list is a relatively easy system to outperform. Can a context system improve upon our current graphical HMD pick chart, and will an automatic context monitoring system be sufficient (in terms of accuracy and detection time) to provide those advantages (and outweigh the cost of the automatic context monitoring system)? As the Wizard of Oz approach in the preliminary study [27] showed variations in performance regarding the reaction time and accuracy of the human wizard, we wanted to use a system that is not dependent on the performance of an experimenter. In industry, laser rangefinders are currently used for monitoring picks [60]. In comparison to infrared sensors, a laser rangefinder (LRF) is more attractive in regards of price (per part bin) and flexibility, which are two important arguments of our approach; thus, we use a LRF for our study.

6.3.1 Task Description

We used the same picking environment and procedures from our first experiment to explore the effect of adding context to the HMD pick chart. Specifically, whenever a pick is detected by the LRF from a requested part bin, this bin is highlighted (using a white background) in the pick chart for the duration of the pick (and, in the case where an image of the part is displayed, that image is inverted). Figure 21 demonstrates how the LRF detects picks and Figure 2 shows the corresponding user interface.

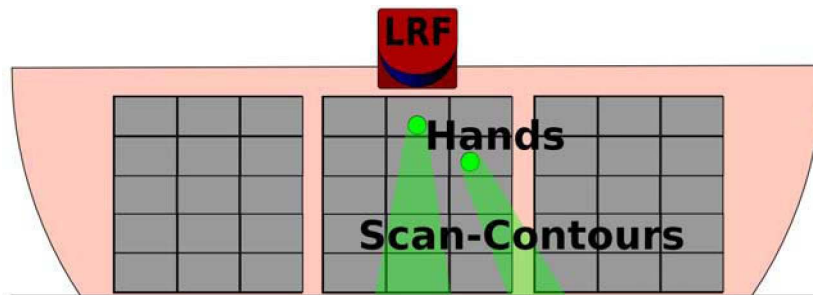


Figure 21: A laser rangefinder detects the worker’s hands as they pass the front plane of the shelving units. An explanation of the approach can be found in [26].

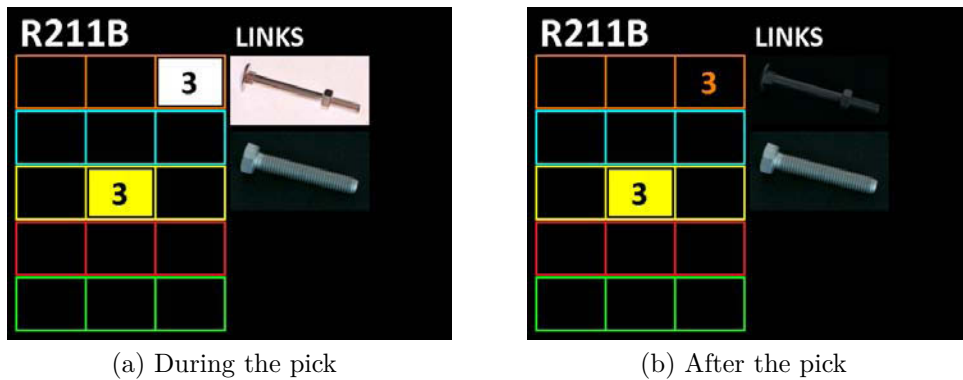


Figure 22: Interface showing pick (CI+LRF)

After the pick is completed the corresponding part bin (and image) is marked as cleared as shown in Figure 22b. In case of a wrong pick – or a wrongly detected pick – the corresponding part bin is marked as a mistake as shown in Figure 23. When the participant reaches again into that part bin, the mistake is assumed to be rectified and the marking is removed. Since pick-detection with the LRF does

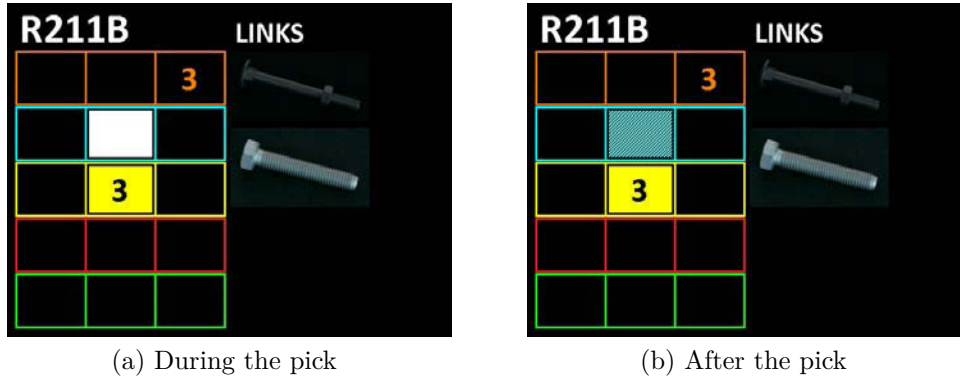


Figure 23: Interface showing wrong pick (CI+LRF)

not work perfectly, we allow the participants to ignore wrong or undetected picks when they believe they have picked all the requested parts correctly.

Based on the reduction in errors in the last experiment, we decided to use colored pick charts only. We also removed the pick chart condition with additional descriptions (*CSD*) since it received the worst feedback from the users. Based on feedback from users in the first experiment indicating that the symbols combined with the images provided “too much information,” we removed the symbols from the *CSI* condition. Thus, we have three pick chart variations (*C* for color, *CS* for color and symbols, and *CI* for color and images). Since our main concern is whether the context provided by the laser rangefinder further reduces errors, we will test six variants: *C*, *CS*, *CI*, *C+LRF*, *CS+LRF*, and *CI+LRF*.

6.3.2 Method

Twelve participants were recruited; eleven participants were right-handed, and ten were right-eye dominant. Four participants wore glasses. One subject had some picking experience from previous employment in a logistic company. All participants completed a training phase as in the last experiment. Each participant performed eight tasks with each picking method during the testing session resulting in 48 tasks (543 picks) for each participant. As in the first experiment, we told the participants to work as if they were in a real occupation and that it is more important to avoid errors than to work extremely fast. In contrast to the first

experiment, we also told the participants that they need to fulfill all tasks of a modality within a fixed time.

6.3.3 Accuracy

Figure 24 shows the errors made for each condition. One mistake within a modality (over all subjects) is equal to 0.0153% mistakes per pick.

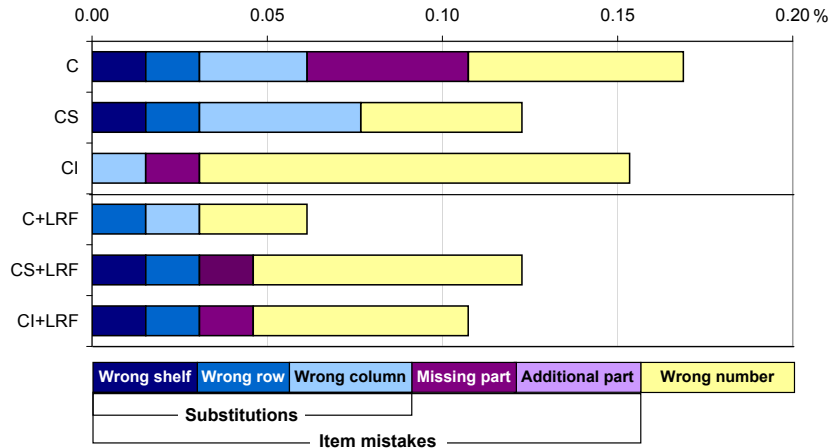


Figure 24: Mistakes/pick in Context experiment

Our hypothesis was that the use of context feedback would improve pick accuracy. Comparing the modalities *With LRF* against the modalities *Without LRF* shows about one third fewer errors for the former. However, a paired, one-tailed t-test results in p-value of 0.13. By its nature, the LRF cannot directly help reduce *Wrong number* errors as it only can sense when the worker’s hand reaches for a bin. In addition, the worker can accidentally trigger the LRF with his head by leaning toward the shelving units or brushing past them while moving, causing false feedback on missing or additional parts. However, the LRF is especially useful in providing feedback for picks that happened on wrong shelving units, wrong rows, or wrong columns. These errors are immediately recognizable on the HMD as the mistake is often adjacent to the correct bin. Comparing these *Substitution* errors in the conditions *Without LRF* context to those *With LRF* context shows a statistically significant improvement ($p = 0.019$; one-tailed, paired t-test). However, the absolute numbers of errors are small: ten errors and six errors, respectively.

6.3.3.1 Post-Hoc Analysis

Examining the results post-hoc, it is noteworthy that the *CI* condition had only one *Substitution* error. Interestingly, the *CI* condition has twice as many errors of the type *Wrong number* than the *CI+LRF* condition (8 vs. 4) and also about twice as many errors of that type than the *CS* (3 errors) and *C* (4 errors) conditions.

6.3.4 Speed

Normalization is performed as in the *Color experiment* but using the average picking speed from the *Color experiment* for convenience. Detailed comparisons across the two experiments is unwise due to the different instructions given and the different participants involved. In fact, participants picked on average 23% faster in the *Context experiment* than in the *Color experiment*. However, the *C* and *CS* conditions are the same across experiments, which allows comparison relative to them and may suggest trends to investigate in future studies.

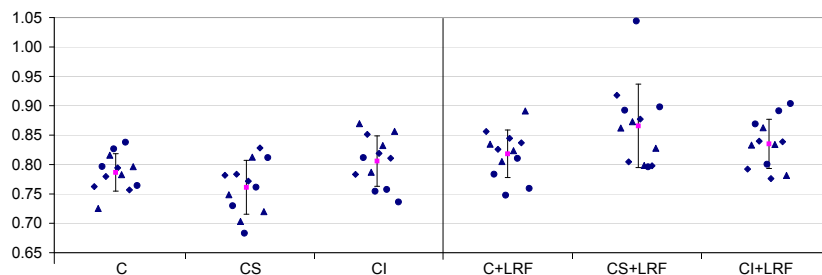


Figure 25: Pick speeds relative to the average (1.00) and normalized to the Color experiment (lower is faster)

The modalities *With LRF* are in average about 7% slower than the modalities *Without LRF* ($p < 0.0001$; two-tailed, paired t-test).

6.3.4.1 Post-Hoc Analysis

When comparing *CI* with *CS* the modality with images is 5.8% slower than the modality with symbols ($p = 0.029$; two-tailed, paired t-test), showing a similar trend as in the previous experiment. Between the modalities *With LRF* there is no significant difference in speed.

6.3.5 Subjective Measures

The *CI+LRF* condition was rated first in all five categories of rankings (see Table 5). Conditions *With LRF* are ranked better than those *Without LRF* across all five categories ($p < 0.05$; Wilcoxon test).

	Without LRF			With LRF		
	C	CS	CI	C	CS	CI
Overall	4.5	5	4	3	3	1
Learnability	5	5	3	3	3	1
Comfort	5	5	4	3	3	1
Speed	3.5	5.5	4	3	3.5	1.5
Accuracy	5	5	4	2.5	3	1

Table 5: Ranking of context conditions (lower values are better)

When asked “*Did you like the use of images for the items to pick?*” participants answered more positively for the conditions *With LRF* than for the conditions *Without LRF* (see Table 6).

	Without LRF	With LRF
Very good	1 Person	7 Persons
Good	7 Persons	4 Persons
Neutral	3 Persons	1 Person
Bad	1 Person	–
Very bad	–	–

Table 6: Feedback from the question: “*Did you like the use of images for the items to pick?*”

Asking the participants “*How well could you find the items to pick?*” the condition *CI+LRF* received the best results: *very good* (8 persons) and *good* (4 persons). The modality *CI* however, was nearly as good: *very good* (7 persons) and *good* (5 persons).

During the open response section of our survey, some participants noted that the pick-detection produces too many errors, which confuses them. Apart from that, the users agreed that working with pick-detection facilitates the process of picking. The highlighting to provide feedback on correct or incorrect picks was

did not work properly. Conditions that used LRF context were slower than ones that did not. The results might have been better if the pick-detection had worked better.

As higher costs are involved with such a system and speed and accuracy of context detection systems might improve, a final recommendation for or against such a system cannot be given here. Further studies should review the benefits and disadvantages of a pick-detection system. Also, a warehouse manager must weigh whether or not such a system is worthwhile in his specific environment. Errors may be so few with the HMD system that the improvement added using a LRF could be considered negligible. On the other hand, in some environments any pick error may be considered unacceptable. Using the observations and experimental techniques described in this paper, pick line designers can perform experiments for their specific situation and balance errors and picking speed versus costs.

Interestingly, for conditions without the use of a LRF, the use of symbols (*CS*) resulted in the lowest error rates and fastest speed. More investigation is needed to determine what role such symbolic cues might play in inventory picking.

Wrong number errors have not been addressed by the variants introduced in this paper, yet they are clearly a major contributor to the overall error rate. One option is to place load sensors in the order bins to measure the number of objects placed and signal when errors occur on the worker's HMD. A simpler option comes from observing the trends from the experiments. In both experiments there have been more errors of this type in the conditions with images or description (within the conditions *Without LRF*). These conditions also trended to be slower. Perhaps interpreting the additional information reduces the user's concentration on the correct amount of items, and placing the number of items that need to be picked above the part's image may help reduce this effect. If such a modification could reduce these errors for the conditions with color and images (*CI*), it might become the best modality to use when pick-detection is not available.

With pick-detection available, the simultaneous highlighting of the box (with

the number of items to pick) and the image may help the user to keep track of the number of items to pick. This assumption is supported by the feedback of the users and reduction of errors between the *CI* and *CI+LRF* condition. However, within the modalities *With LRF* the condition *C+LRF* showed the fewest errors. Assuming a perfectly working context detection system, this result becomes obvious, as people should then be able to concentrate more on the feedback from the context detection system. Still, the participants liked to be supported by images in an unknown domain.

The navigation of the picking client was found to be good. The animation showing a shelving unit change⁴ was mostly liked and was perceived to be helpful. However, there were still some mistakes of the type *Wrong shelf*. Therefore, it might be useful to prompt the user explicitly for a change of the shelving unit (especially for modalities without the use of pick-detection and images).

In general, the low number of errors in the study makes comparisons difficult. We had to add more variety to the pick tasks than in our previous studies in order to elicit even the few errors seen here. In many senses, this situation is encouraging. From industrial environments, we know that pick-by-light systems are very successful in speeding up picking and eliminating errors; yet they are expensive. HMD-based systems could offer a lower cost alternative, and our previous studies have shown they can be fast and accurate. The obvious next step is a direct comparison between the two techniques.

⁴By showing an arrow in front, moving the pick chart from the left side of the screen to the normal position (similar to the animation as shown in Figure 35a in Chapter 7).

Chapter VII

USAGE IN AN INDUSTRIAL ENVIRONMENT

This a compilation of the papers and poster (with me as first author) presented at the ISWC 2012 conference and the accompanied *Workshop on Wearable Systems for Industrial Augmented Reality Applications* [6, 7, 8].

7.1 Introduction

In previous studies, we focused on carefully-controlled, internally-valid studies comparing the speed and accuracy of various versions of mobile order picking systems. However, such studies lack the ecological validity of testing on a manufacturing line with experienced employees fulfilling actual orders under time and accuracy constraints. Therefore, we planned a user study in the assembly plant of Daimler, a large automobile manufacturer. Originally, the study was planned at Daimler in Mannheim where the workers often move away from the pick cart. For this setup I planned to evaluate a wrist-worn device as another display technology in comparison to the HMD. As the study in Mannheim was canceled due to objections of the works council, I decided to perform the study at Daimler in Bremen. In the setup in Bremen the workers are always next to the pick cart, which is moved on rails. Accordingly, to use a tablet PC instead of a wrist-worn device was reasonable.

This chapter presents the results of the user study at Daimler comparing the pick-chart, on a wearable computer with a HMD or a tablet PC, against a text-based pick list and an established and highly efficient pick-by-light system. The evaluation focuses on user acceptance and workload of experienced workers but also examines error-rates and picking speeds with these systems. In addition, we discuss our experiences from planning and conducting a study in a large automobile company.

7.2 Difficulties in Planning and Preparing

In planning a user study on an operating assembly line in an automobile company, many departments and individuals are involved, including the manager responsible for selecting technologies, workshift-leaders of the picking facility, the works council (the works council consists of the plant's workers' representatives who are involved in the working conditions and rights of workers), IT departments, and more. Each stakeholder focusing on different interests must be included. Integrating into the existing infrastructure required many agreements with different IT departments of the company. We also needed to interface with the IT-infrastructure of an external company responsible for the pick-by-light and pick-detection system.

7.3 Task and Picking Environment

Figure 26 and 27 illustrate the picking environment. The rectangles labeled *1XX* to *8XX* indicate the shelving units; *GLT 1* to *GLT 8* are large load carriers (GLT) for larger items. The pick cart runs on rails between the two rows and has four order bins, one for each car being assembled (see Figure 27a). Each shelving unit has three rows for picking. Typically the upper and middle row have three pick (and three pick-by-light) locations, while the lower row has typically two pick locations. As parts change over time and the width of the boxes in the shelves vary, some unused pick locations may be partly consumed by a bigger box from a bordering pick location.

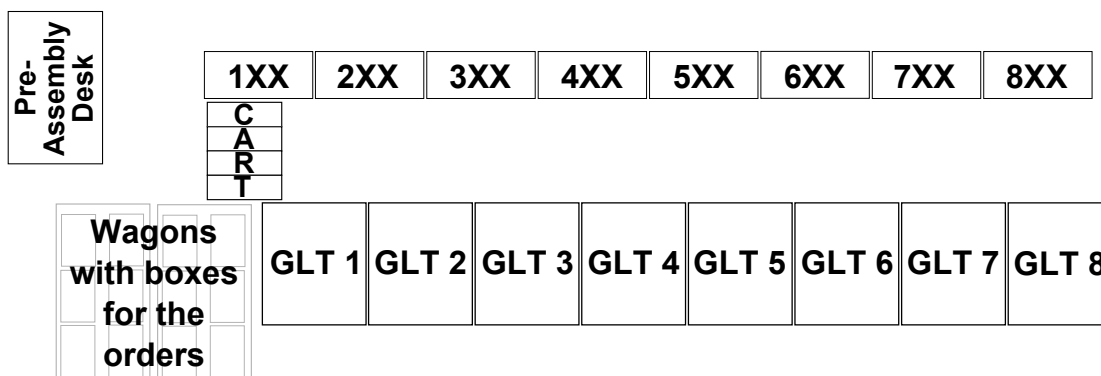


Figure 26: The picking environment

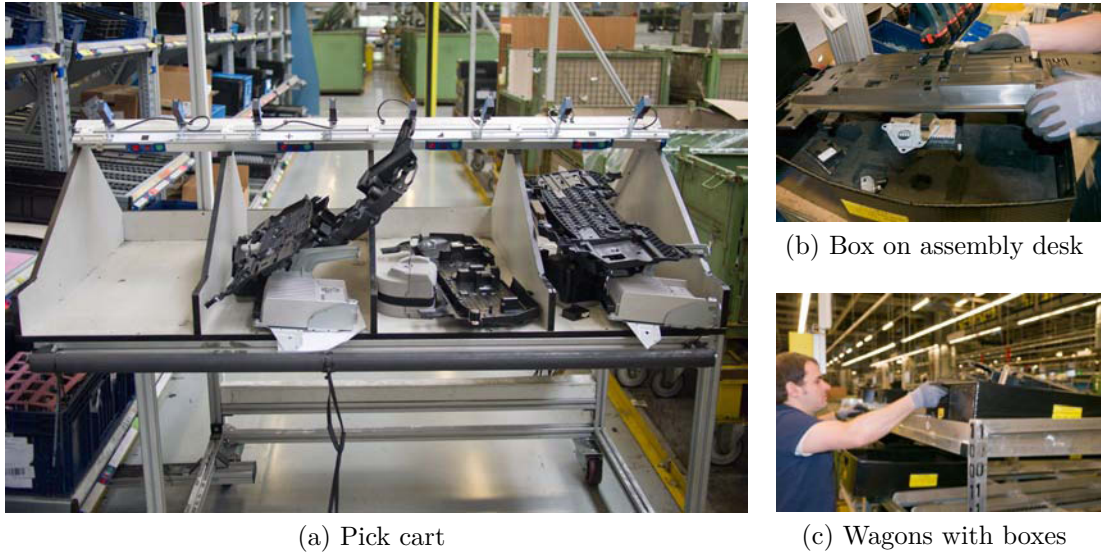


Figure 27: Images from the picking environment

We used the same pick- and put-detection sensors normally used by the Safelog pick-by-light system [60]. Laser range-finders (LRF) mounted in front of the normal shelving units and large load carriers detect picks. Two infrared sensors over each order bin detect puts on the pick cart. Every pick location and order bin has a pick-by light unit with an integrated button which could be used as an alternative to the automated pick- and put-detection (in case a pick or put was not detected automatically).

A worker completes four orders at once. Print-outs of the next four orders are placed into the order bins in the pick cart, independent of the picking method used. When the worker starts a pick task, he confirms that the next orders correspond to the orders noted on the prints in the picking cart. Next, he pushes the pick cart along the shelves, picking all items necessary for the four orders using one of the picking methods described in Section 7.4. When finished, he returns the pick cart, retrieves an empty box for each order from a nearby wagon (Figure 27c) and fills that box with the corresponding items. Some items are assembled while filling the orders (Figure 27b). The picker has the option to verify the picked items with the order print-outs. After placing the filled box on the wagon, the participant is ready to continue with the next task.

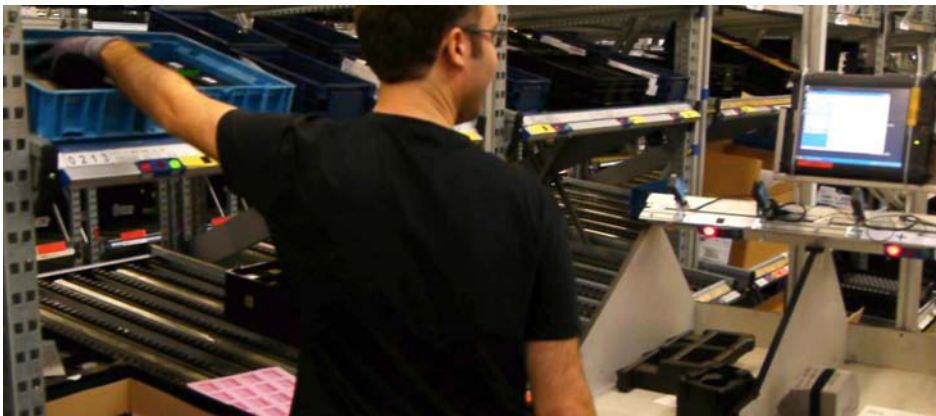
7.4 Picking Methods

7.4.1 Pick-by-light

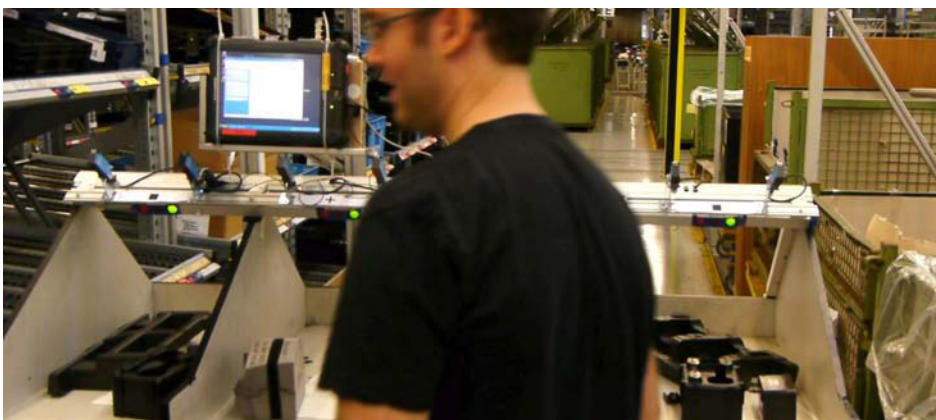
Pick-by-light is the usually used method at the concrete setup. Figure 28 illustrates how picking with pick-by-light is generally performed. With the exception of the



(a) A red light indicates the next pick location



(b) After pick-detection, the light turns green and red lights on the pick cart indicate where to put the items (and how many items are needed in total)



(c) After every put the corresponding light on the pick cart turns green (the next pick location is shown after the last put of the previous item)

Figure 28: Pick-by-light

items at pick location 113, items are needed only once per order. If required, the items at pick location 113 are needed two times per order. This detail is known by all workers on this line, and thus the total amount of items needed can be inferred by the amount of lights displayed on the pick cart.

7.4.2 Pick-by-HMD

For pick-by-HMD, workers wear a vest with a teXXmo TX-1000 Wearable PC using a 1.6GHz Intel Atom Z530 and 1GB of RAM (Figure 29a). Pick charts are displayed on a MicroOptical SV-6 (an opaque, monocular HMD) mounted on safety glasses with the lenses removed. Independent of the eye dominance, the HMD was always worn over the worker's right eye.¹ To compensate the weight of the HMD, we added a counterweight to the left side of the safety glasses. A Vuzix rugged mouse with two large buttons allows navigation and is carried vertically near the right hip (Figure 29b) or is attached to the pick cart and connected wirelessly. Section 7.5 describes the pick chart variations tested.



(a) Back: wearable computer, HMD electronic, battery, wlan-antennas



(b) Front: rugged mouse and battery status LED

Figure 29: Pick-by-HMD

¹An explanation why we decided to use the right eye can be found in Section 8.4.4.

7.4.3 Pick-by-tablet

For testing pick-by-tablet, a tablet PC and the Vuzix mouse were attached to the pick cart for testing. We started with a teXXmo Kaleo GX tablet PC but soon switched to an xplore iX104 tablet PC due to instability in the graphics during animations. For pick-by-tablet we used the same pick chart variations as with pick-by-HMD (see section 7.5).



Figure 30: Pick-by-tablet

7.4.4 Pick-by-paper

Two slightly different pick-by-paper variations (Figure 31) were printed on DIN-A4 sized paper. I developed these variations based on feedback from the workers and by concentrating on the most important informations the workers need to fulfill their tasks. The top row shows the orders of the current task (in Figure 31, order 74, 75, 76 and 77). The leftmost column shows the pick locations of the items needed for the orders. In Variation 1, in addition to the pick locations, the total number of needed items is shown after the prefix “x” (in cases where in total the amount is more than just one item). The four following cells show the number of items needed for the corresponding order.

20110902T077				
	074	075	076	077
113 x 2			2	
123			1	
133 x 2		1		1
1			1	
213 x 3		1	1	1
223	1			
2			1	
331	1			
3	1			
423 x 2	1			1
421 x 2		1		1
4	1			
511 x 2		1		1
613		1		
612 x 2		1		1
622		1		
6	1			
8 x 2		1		1

20110902T077				
	074	075	076	077
113			2	
123			1	
133		1		1
1			1	
213		1	1	1
223	1			
2			1	
331	1			
3	1			
423	1			1
421		1		1
4	1			
511		1		1
613		1		
612		1		1
622		1		
6	1			
8		1		1

(a) Variation 1

(b) Variation 2

Figure 31: Pick-by-paper

7.5 User Interface and Variations

To start a new task, the worker double-clicks the *forward-button* on the mouse (the other mouse button was defined as the *backward-button*). The first screen of the task appears showing the current order numbers (see Figure 32a). The user verifies the order numbers with the prints in the four order bins. With another forward-button press, the picking procedure starts. After all parts of a task are finished, a final screen informs the worker that he is ready for the next task (see Figure 32b).



(a) First screen of a task

(b) Final screen of a task

Figure 32: First and final screen of a task

7.5.1 Pick step and Pick chart visualization

A pick task is divided into pick steps. A pick step consists of either: *one pick location and all corresponding receiving bins* or *one receiving bin and all corresponding pick locations of the current shelf*. If optimization is not used (see Section 7.5.4), the first variant is always used (corresponding to the normal ordering of the pick-by-light system). Every pick step displays on a separate screen. We tried two slightly different pick chart visualizations. The *abstract visualization* (Figure 33a), displays every existing pick location independently of the currently used boxes and box-widths. For the *concrete visualization* (Figure 33b), location and width of the boxes were considered, and unused pick locations were not shown.

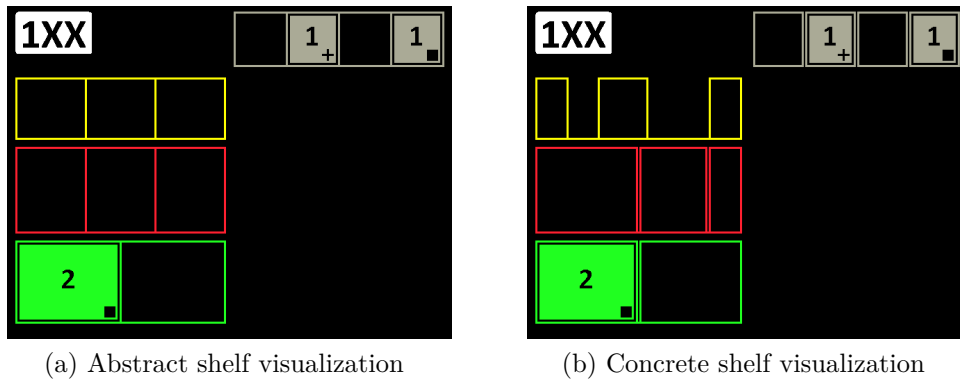


Figure 33: Shelf visualization

In the pick chart in Figure 33, the shelving unit identifier ($1XX$) is shown at the top-left of the screen. If this identifier is black with a white background, then the previous pick step was from a different shelving unit. The pick chart shown indicates that the worker should pick two items from the bottom-left box of the shelf and put them into the second and fourth order bin of the pick cart (order bins are shown in gray on the top-right of the screen). The colors and symbols on the pick chart correspond to labels shown under each box on the physical shelves or over the order bins on the pick cart.

7.5.2 Picking procedure, pick- and put-visualization and shelf changes

To complete a task, a worker must complete all pick steps as they are presented to him sequentially. If pick-detection is used, a part bin is highlighted in the pick chart during a correct pick (Figure 34a). Afterwards, the part bin reverses background and foreground color to indicate that the part was correctly picked (Figure 34b). A reach into a wrong part bin highlights the incorrect part bin in the pick chart (Figure 34c). Afterwards the part bin gets normally visualized like before. Put-detection was used during the whole study. During a put, the corresponding order bin in the pick chart is highlighted and reversed afterwards (Figure 34d).

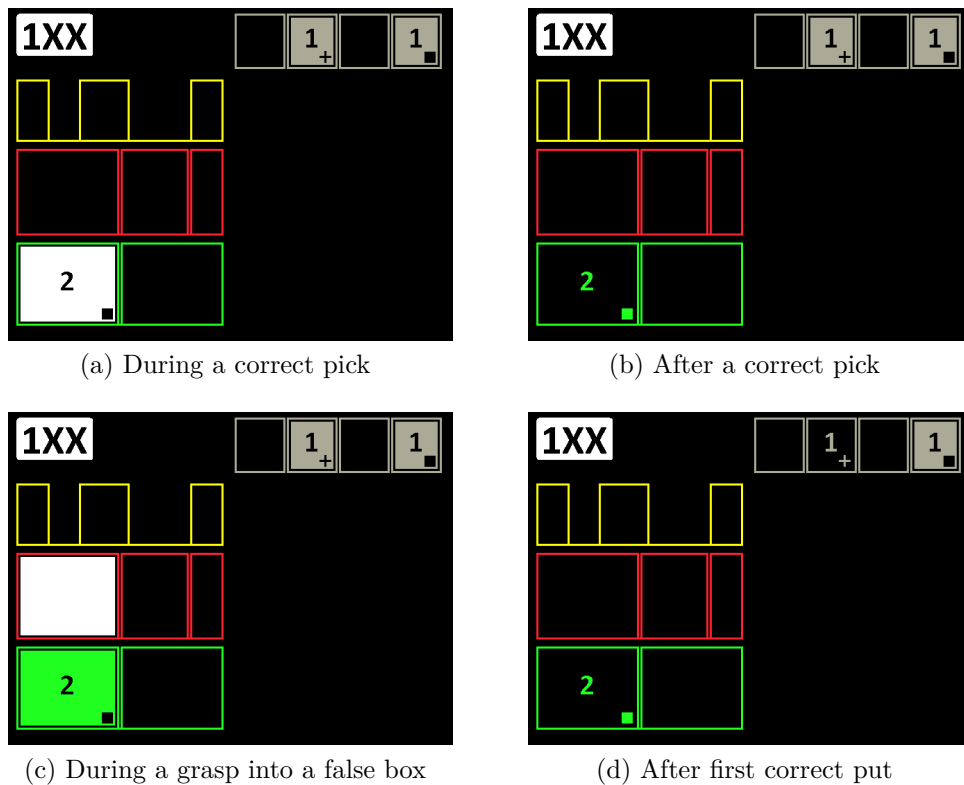
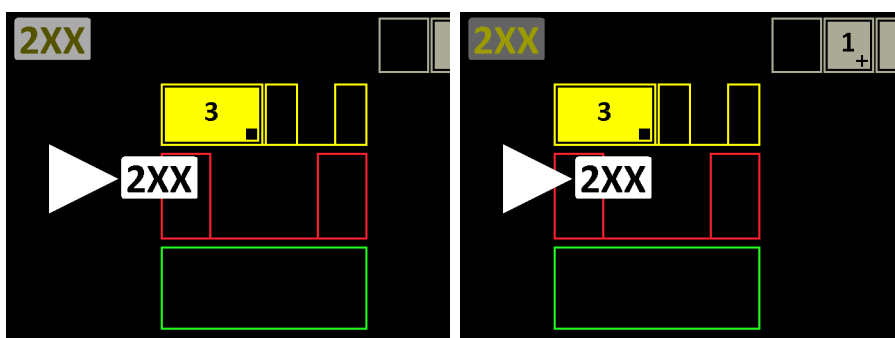


Figure 34: Pick-detection

A pick step is finished when all picks (when pick-detection was used) and puts of the current pick step are detected. After a pick step finishes, depending on the setting used, the system either switches to the next pick step automatically or the worker has to press the forward-button. If the next pick step is within the same

shelf as the previous pick step the next pick step will be shown instantly. If the next pick step is within another shelf, depending on the setting, the system will

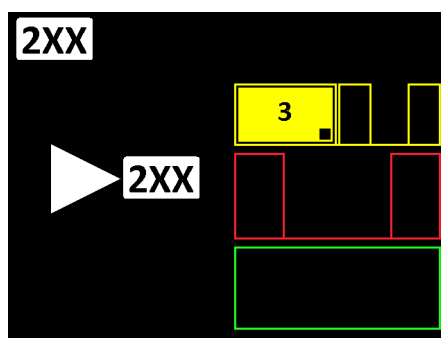
- show an animation with an arrow and the shelf identifier in front, moving the pick chart from the left side of the screen to the normal position (see Figure 35a),
- show an additional screen asking for user confirmation (see Figure 35b),
- show an arrow and the shelf identifier on the left side and the pick chart on the right side (see Figure 35c). For this variation, after a confirmation or a detected pick from the correct shelf, the arrow and shelf identifier disappear and an animation moves the pick chart to the normal position.



(a) Shelf change with animation



(b) Shelf change with extra screen requesting confirmation



(c) Shelf change with translated pick chart

Figure 35: Shelf change

If a worker wants to check a previous pick step, he can page back through the pick steps with the backward-button (a green dot indicates previously finished pick steps). Afterwards, the worker pages forward through the pick steps with

the forward button until he reaches again the last shown and unfinished pick step, indicated with a gray dot. The system does not allow paging forward through unfinished pick steps.

7.5.3 Part Images

Optionally, part images could be shown on the right side of the screen (see Figure 36a). To ensure that the worker attends the number of items to pick (this problem was observed in our previous study and is discussed in Section 6.4), the number of items were rendered at the bottom-right of the part image in the color of the corresponding row. Additionally, the system shows one or more exclamation points behind the number of items for the parts where similar parts exist, to avoid an accidental substitution of these parts (see Figure 36b).

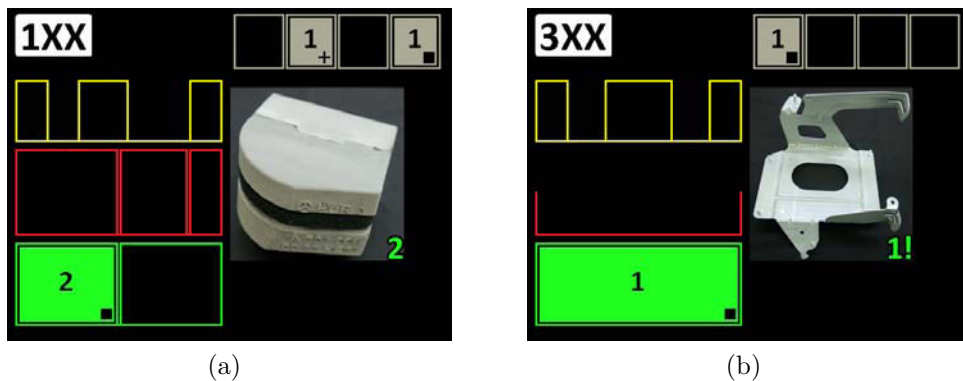


Figure 36: Visualizations with object images

7.5.4 Optimization and audio feedback

If optimization is switched on, the system compares the amount of movement required for a shelving unit using a policy of either displaying *one pick location and all corresponding receiving bins* or *one receiving bin and all corresponding pick locations*. The worker is prompted with the shortest combination of movements. In the pick task shown on the paper pick list (Figure 31), for example, two optimizations would be possible: one within the shelving unit 1XX (showing pick location 113 and 123 at once for order 076), and one within shelving unit 6XX.

Optionally, we could turn on audio feedback for the pick- and put-detection. Whenever a correct pick or put was detected, a short audio sample was played as feedback.

7.6 Method

Due to policies regarding the capture of employee performance, anonymity was requested and video recordings, questionnaires and explicit records of time measures were not permitted. Our research methods used in the previous studies had to be modified significantly. Therefore, we used simplified qualitative methods like open questions to discover previously unknown facts as well as elements of ethnographic study (e.g. observing the behavior of the subject while working with the picking solution).

We emphasize the significance that the picking facility provides parts directly to a running assembly line process, where interruptions within the supply chain had to be avoided. Orders need to be picked and pre-assembled continuously to satisfy the demands of the assembly line. For this reason, no special training sessions are possible, and the workers need to fulfill the demand of the picking-line with the wearable or the tablet solution from the beginning. Experimenters support the subjects at the beginning of each condition and also explained the system in more detail while the first tasks are performed. On demand, experimenters also help with secondary tasks to reduce the workload and time pressure for the worker.

Worker participation in the study is based on agreeing to try the wearable or tablet solution. To encourage feedback and insure cooperation, we present different variations of the interfaces to the worker and always let him use the combination which he prefers. However, we encourage workers to try at least a few tasks (a task consisted of an average of 15 pick steps in the unoptimized conditions) with each variation to allow familiarization.

To gather user feedback without violating any policy constraints, the subject

was asked to provide feedback regarding the general method and the current interface variation while he was performing non-order pick tasks such as pre-assembly, secondary activities or during his personal allowance time. Based on the experimenters' observations and subjects' feedback from memory, experimenters wrote notes for later evaluation. After the worker tried a first method, the experimenters asked him to try the other pick-chart-based method or one of the pick-by-paper variations.

As experimenter I was always (with exception of a few breaks) at the picking line if one of three methods (pick-by-HMD, pick-by-tablet or pick-by-paper) was used. I was responsible for detecting errors and ensuring that everything worked as expected. To avoid losing time, we provided a means for quickly switching back and forth between our methods and the normally used pick-by-light system. I added a low-battery warning and hot-swapping capability for the wearable computer's battery packs to allow continuous operation. A second experimenter² supported me in observing, asking questions, taking notes, discussing observations, etc. When necessary a third experimenter³ was available to support us.

The study had a duration of four weeks. Seven experienced workers used pick-by-HMD, and eight experienced workers used pick-by-tablet. Five workers tried both methods. Pick-by-paper was used by four workers (all of whom used at least one of the other methods).

7.7 Accuracy

We intended to compare two different types of errors: mistakes noticed by the experimenters or the worker himself before the order left the picking line and mistakes detected by quality management after the orders left the picking line. Fortunately, no errors were observed by quality management; thus, we focus on the former class of mistakes.

During the shorter observation periods dedicated to the pick-by-light method

²Patrick Zschaler from Daimler AG, Plant Mannheim

³Hendrik Iben, a colleague of mine

(about 50 tasks), no mistakes were observed on the picking line. However, 2 mistakes were observed during the 276 tasks (corresponding to 4016 pick steps, 4459 picks⁴, and 5839 puts) performed using pick-by-HMD. No mistakes were observed during the 113 tasks (1847 pick steps, 1855 picks, and 2655 puts) performed with pick-by-tablet. At least one error was observed in 10 of the 16 (non-training) tasks that used paper pick lists. Of the four workers who tried pick-by-paper, all committed errors on at least 50% of their tasks. Omitted parts were the main errors with paper pick lists, as workers had difficulty keeping track of their progress. Thus, while mistakes might decrease as workers gain more experience with pick-by-paper, we feel quite sure that pick-by-paper would have shown significantly more errors than all the other methods in a controlled study.

7.8 *Speed*

Due to requirements for protection of data at the plant, we can only report our subjective observations regarding picking times. Initial tasks using pick-by-HMD definitely needed more time than with the normal pick-by-light system. When first introduced to the HMD, every participant needed some time to adjust its focus and position. Most workers tried to optimize these HMD settings several times during their first tasks. Focusing and reading from the HMD also seemed to be slower at the beginning (many subjects looked strained reading the HMD). A few subjects also required some time to accustom themselves to the pick chart concept. One subject needed a few seconds to interpret the pick chart correctly for every pick step at the beginning. While after a few tasks the process improved, the worker definitely was not able to achieve the same speed as with pick-by-light (though he did not try using part images with pick-by-HMD). To compensate for the increased picking times – as already noted before – experimenters helped the subjects with some secondary tasks.

One subject used pick-by-HMD for three weeks and most working days between

⁴Without optimization, the number of picks equals the number of pick steps.

four hours and a whole work shift (8 hours). Given this practice, the subject was able to perform the work easily without the need of help. Another subject who used the system for over 4 hours/day for two days was able to fulfill his work without the need of support. However, he seemed to have more time pressure than when using his normal pick-by-light system. Given our observations, we suspect that pick-by-HMD is slower for novices than pick-by-light but that the difference will narrow with practice, with pick-by-light still being faster. It should be noted that the workers were pick-by-light experts, giving that method an unfair advantage. A more controlled study is needed to determine the relative speeds of both systems more accurately.

With pick-by-tablet, most workers were quite fast from the very beginning and further improved their speed after some practice. As with pick-by-HMD, a few subjects needed some time to adapt to the pick chart. The subject who was slower in interpreting the pick chart with pick-by-HMD also needed notably more time for interpreting the pick chart using pick-by-tablet. However, when we used the extension with part-images he became notably faster, achieving a speed comparable to the other workers.

In comparison to the other methods, we saw that at the beginning pick-by-tablet was slower than with the worker's normal pick-by-light system, but faster than beginning with pick-by-HMD. However, with expert usage, we suspect that pick-by-HMD could be faster than pick-by-tablet as the HMD allows the worker to glance at the pick chart at any time as opposed to repositioning his head to see the display on the pick cart.

Pick-by-paper seems to be a little slower than the other methods. When the worker got confused – for example in remembering which line he completed in his last pick (which happened quite often) – picking times increased even more. However, we observed a very high error rate with pick-by-paper, which is a much more important component than speed for most pick tasks.

7.9 User Acceptance and User Feedback

In the following sections, we collect user feedback and our observations on user acceptance for the different methods. In general, workers liked the current pick-by-light system, with the exception that the automatic pick-detection is partially disliked as sometimes picks or puts are not detected. More rarely, picks or puts are detected when there was no pick or put (for example, when the worker's clothing brushes past a sensor).

User feedback regarding the interface variations was comparable across the devices (HMD and tablet). The first subjects had a preference for the concrete visualization over the abstract visualization and highly preferred the automatic transition to the next pick step over pressing the forward-button on the mouse. To reduce the amount of parameters, we decided to continue with the concrete visualization and the automatic transitioning for the rest of the study.

After some practice, all participants preferred the animation showing the change in shelving unit. For a few subjects, we believe that the variation with the additional screen requiring an explicit confirmation for the shelving unit change was helpful to become accustomed to the new picking method.

Part images were preferred by most subjects, but some participants preferred to work without the part images as the images distracted them slightly. Two subjects said that they mainly used the images for orientation, as they already knew all pick locations for the items.

At the beginning of the study we used the pick-detection system as we wanted to minimize the risk for mistakes. As we observed that all subjects (after a little practice) picked very reliably from the correct part bins, we decided in the last 1.5 weeks of the study to allow subjects to try pick-chart-based methods without pick-detection. Remarkably, while pick-detection was turned off, no mistakes were made, and all subjects preferred to work with the pick-detection turned off (subjects felt that their work flow was interrupted when pick-detection did not detect a pick instantly).

All subjects except one preferred to have audio feedback for every detected put (and pick, if pick-detection was used). Optimization was tested by three participants. Two preferred to work without optimization as they felt that having a consistent work flow was easier. In contrast, the remaining subject liked the optimization. Given the variations observed among workers, we suggest that pick-chart-based systems include a set of user preferences to allow personalization of the interface.

7.9.1 Pick-by-HMD

Workers were highly skeptical about the appearance of the wearable computing hardware, and it reflected in their willingness to participate. Many workers tried to avoid the picking line during our study, and four of the workers who needed to work at the picking line refused to try the pick-by-HMD solution. Some of the workers even tried to convince other workers not to try the pick-by-HMD solution as some of them were generally afraid of innovations which may bring drawbacks for their future (through worse working conditions, higher workloads, etc). These influences might have affected the subjective awareness of the workers who agreed to try the pick-by-HMD (and also pick-by-tablet) approaches.

From our estimation, before starting to use pick-by-HMD, only two subjects had a neutral attitude, four subjects had a more negative attitude, and one subject had a very negative attitude towards the use of pick-by-HMD. When starting, all participants stated that pick-by-HMD causes some eye-strain. Five subjects complained of problems such as: difficulty in seeing the HMD-image, eye pain or concentration problems. Three subjects felt physically restricted wearing the equipment, and one subject mentioned that he started to sweat wearing the vest. One subject said that he is slower with pick-by-HMD than with pick-by-light, causing him time pressure. For these reasons most subjects stopped using the pick-by-HMD approach before they had a chance to grow accustomed to the HMD.

One of the subjects with a neutral attitude (wearing varifocal glasses, but switching to his old normal glasses after some time) used pick-by-HMD for a longer

time (about 4 hours/day for two days). He reported some adaption to the HMD but stated there were still problems reading the HMD when looking into bright or inhomogeneous backgrounds. He also said he would prefer a bigger screen on the HMD. Except for the eye-strain, he liked the system and could imagine working with an improved pick-by-HMD solution.

Another subject (wearing glasses) with a neutral attitude at the beginning used the pick-by HMD system also for two days (4 hours/day). The subject felt restricted in his movements and clearly preferred pick-by-light over pick-by-HMD. For pick-by-light this subject reported a very low eye-strain and a low overall workload. For pick-by-HMD in comparison, he reported a high eye-strain and overall workload.

The only subject (not wearing glasses) who used pick-by-HMD over a longer time (over three weeks and most working days for at least four hours) changed from a more negative attitude at the beginning towards a more positive attitude regarding pick-by-HMD. The first three days the subject used pick-by-HMD for short periods, reporting eye-strain. As he was also our first subject, other workers watched and commented on the HMD approach. As a result the subject claimed that *All are watching, and I am looking like a Martian*. From the fourth day on the eye-strain got much better, and the subject used pick-by-HMD for about four hours. After 1.5 weeks, eye-strain was finally gone, and the subject could work over whole shifts (8 hours) using pick-by-HMD without any problems. The subject reported that the overall workload was only a little higher than with the pick-by-light setup.

7.9.2 Pick-by-tablet

With exception of one subject (who feared that new technologies might negatively affect his future, causing a very negative attitude towards the use of pick-by-tablet), all subjects gave a neutral or positive response with regard to the use of pick-by-tablet. All subjects who also used pick-by-HMD preferred the tablet.

One subject noted that he prefers pick-by-tablet over pick-by-light. Another

subject who initially showed a negative attitude towards pick-by-tablet, stated afterwards: *If I would have known that the system works so well, I would have taken part before. That system would be great at our big pick-by-light set. There you have to do 16 orders at once, and if your hand accidentally hits one active box the system switches to the next part without having the ability to go back to check the last step.*

7.9.3 Pick-by-paper

Every worker who used the paper pick list mentioned quickly that it required much higher concentration and resulted in many more mistakes than with the other solutions. No one preferred to work with pick-by-paper, and soon everybody switched back to another method.

7.10 Discussion

Unlike our previous studies, the restrictions at the plant precluded a quantitative evaluation. We still gained much information about user acceptance and the performance of the tested methods, but making an objective and comprehensive evaluation is difficult. While this fact is not encouraging (especially considering the much larger effort needed compared to a study in a laboratory), we still believe that the study was valuable. We had many quantitative results from our previous studies showing the advantages of pick-by-HMD, but we still had no idea how experienced workers would accept this method. While we expected a high amount of skepticism regarding new technologies like HMDs, the study revealed that we still underestimated it and the corresponding effects resulting from the reluctance of some workers. Reasons for the skepticism and reluctance might be that they are used to their pick-by-light routine as a fast and accurate method⁵ and that

⁵In our previous studies we never compared against pick-by-light. The methods to which we compared before – pick-by-paper and pick-by-voice – probably have a higher workload than pick-by-light. If we expect participants to report workload (and eye-strain) relative to the other methods they used, this would mean that in this study the relative workload and eye-strain (compared to the other known methods) was indeed higher even if the absolute workload and eye-strain was still the same.

workers are sensitized regarding negative effects that might affect them from such a new technology. The situation was confounded by existing group dynamics between the workers, who influenced each other by loudly denigrating the wearable computer's appearance and other aspects. This result underscores the importance of establishing a plan (including social-psychological aspects) on how to introduce a new technology to a current process. Siewiorek, Smailagic, and Starner [64] provide a case study in how Symbol (now Motorola) successfully introduced their arm-mounted wearable computer in similar industrial environments.

Overall user acceptance for pick-by-light and pick-by-tablet were quite positive whereas user acceptance for pick-by-HMD and pick-by-paper lagged far behind. Even after some workers tried pick-by-HMD, the approach had difficulties with user acceptance. Many workers reported – especially at the beginning – a higher workload and eye-strain. More experience with HMD usage and personalized fitting of the HMD to the individual worker's face may help offset these issues (for example, at least two workers were left-eye dominant, which may have made seeing the display more difficult). Pick-by-paper, meanwhile, was discarded outright as causing too many errors. Pick-by-tablet, in contrast, was much better accepted directly from the beginning, and all workers – with exception of one worker – could imagine working with such a system.

With respect to error rate, pick-by-light, pick-by-HMD and pick-by-tablet perform very well. Pick-by-paper, in contrast, lags far behind the other methods. Pick-by-tablet and, even more, pick-by-HMD showed slower speeds than the established pick-by-light method at the beginning. However, after some practice, workers' speed improved and was similar to pick-by-light.

Pick-by-tablet and pick-by-HMD virtually eliminate errors, even when pick-detection was turned off, which was preferred by the users. Given the results here and in previous work, eliminating the pick-detection system would seem to lower cost further, improve user acceptance, and have little effect on the pick

quality. In contrast, a put-detection system on the pick cart could be implemented with a much smaller investment and allow a reduction of errors (of the type putting/placing into a wrong order bin) and an automated transition to the next pick step when the previous pick step is finished. Workers definitely desired this latter feature. As pick-by-tablet compares quite favorably to pick-by-light in terms of investment costs and shows a similar performance, I am convinced that it could be used beneficially at many picking scenarios.

Chapter VIII

DISCUSSION

8.1 Connection and Summary of Studies

Our first study, which was briefly discussed in Section 4.2, showed that (in comparison to a text-based paper pick list) the proposed wearable computing solution with a head mounted display and a textual and context-sensitive visualization of picks reduced the number of errors where context sensitivity was applied. While speed was improved, the evaluation of this study showed that this advantage was mainly due to an optimized ordering which reduced the required travel distances compared to the paper pick lists. From this study we also learned how to improve the study design, making performance differences between different modalities more measurable and comprehensible. Another conclusion of this study was to switch to another HMD as the Trivisio M3 color see-through HMD was difficult to read for most participants and also occluded much of the user's field of vision (see Section 8.4.1).

In the next study, discussed in Chapter 5, we changed the study design, switched to a MicroOptical SV-6 HMD – although knowing that no longer at purchase – and introduced the pick-chart-based user-interface. We compared the pick-chart-based user-interface shown on the SV-6 HMD to a text-based paper pick list, pick-by-voice and a paper pick list using the same pick charts as shown on the HMD. In contrast to the previous study, we deliberately did not use context feedback, as we wanted to evaluate how the graphical representation performs without any additional context feedback. The evaluation of this study revealed that:

- the method using the HMD was significantly faster than all other methods,

- the method using the HMD had the fewest errors and significantly fewer errors than the text-based paper pick list,
- the HMD method was preferred to the other methods (statistically significant),
- comparing the text-based paper pick list and graphical paper pick list, we concluded that the graphical paper pick list works better than the textual representation,
- the method using the HMD works better than the method with the paper using the the same graphical pick charts as the HMD method,
- while the overall error rate of the method using the HMD was very low, picking from the wrong row of a shelf was the error that occurred most often.

The improved study design was a success. However, for the next study I planned to increase the complexity and variation of the pick tasks to encourage higher error rates to better compare the methods.

When we interviewed managers at Daimler, we were told that errors are the most important concern. Pick errors can stop an assembly line, creating large losses. Thus, my next aim was to develop extensions for the user-interface that help to reduce the error-rate. Correspondingly, the goal of the work presented in Chapter 6 was to identify which of the developed variations might most benefit the planned industrial study, as opposed to variations that might cause insignificant improvements or actually have negative effects. Summarizing the results of this study:

- Using color for the rows:
 - reduced error rate by 58% (statistically significant),
 - was preferred (statistically significant),

- showed about the same speed as the monochrome variants.
- Using symbols for the columns:
 - showed a slightly positive trend.
- Using images resulted in:
 - more errors of the type *Wrong number*,
 - fewer *Item mistakes*.
- Context feedback:
 - resulted in fewer errors (about 1/3 fewer errors but the result did not achieve statistical significance), and a reduction of errors where context feedback directly helps to detect errors ($p < 0.05$, without Bonferonni correction)
 - resulted in slower task times ($p < 0.0001$, without Bonferonni correction),
 - was subjectively preferred ($p < 0.05$, without Bonferonni correction).
- Overall we received very positive feedback regarding the usability of our solution.

While the results were quite promising, we did not know how experienced workers would accept the solution and also wanted to evaluate for issues that might result from usage over a longer period (whole working days over at least a few weeks). Thus, the next aim was to conduct a study in an industrial environment – in our case at Daimler – with experienced workers under normal working conditions. From the results of the previous studies we expected a clear advantage regarding the performance of our pick-chart-based solution compared to picking with paper pick lists. We also wanted to compare the performance

compared to pick-by-light, as this comparison is important when deciding which picking technology is most appropriate (economical) for a specific picking line.

As the study discussed in Chapter 5 showed that the pick chart is a key for achieving high performance, we wanted to see how pick-by-HMD (as discussed in Chapter 7), compared to a pick-chart-based solution using another display technology: a tablet-PC mounted to the pick cart (pick-by-tablet).

The study focused on user-acceptance and (due to stakeholder restrictions at the plant) used simplified qualitative methods like open questions to discover previously unknown facts as well as elements of ethnographic study (e.g. observing the behavior of the subject while working with the picking solution). Below is a summary of our qualitative observations:

- The accuracy of pick-by-HMD and pick-by-tablet was much better than pick-by-paper and close to pick-by-light.
- The speed of pick-by-HMD and pick-by-tablet tended to be better than pick-by-paper and was close to pick-by-light.
- Workers preferred different variants of the interface (the use of images, sorting optimization etc.).
- Working without pick-detection was preferred. Sometimes pick-detection did not detect the picks immediately and thus working without pick-detection allowed for smoother operation. While pick-detection was turned off, we did not detect a single mistake; but depending on the scenario and the performance of the pick-detection solution I would expect a slight improvement in accuracy with a pick-detection system. In most cases I expect the accuracy without pick-detection is sufficient (being close to zero), and in most scenarios I would expect that a solution without pick-detection will be more economical because of the lower investment costs.
- Put-detection was preferred by workers. It reduced the risk of placing an item into the wrong order bin and allowed for an automatic transition to

the next pick step. Thus I would recommend it, especially as it does not increase the investment costs and operating costs significantly.

- The user feedback and user acceptance for pick-by-HMD was poor.
 - At the beginning reading from the HMD was strenuous and slow and many participants reported eye-strain or headache.
 - Wearing the wearable-vest was disliked by workers.

I suppose that participants who are used to work with paper pick lists (instead of pick-by-light), might have been more receptive to the HMD as a better alternative.

- The user feedback and user acceptance for pick-by-tablet – using the same graphical representation as pick-by-HMD – was much better and comparable to the normally used pick-by-light setup.

8.2 Goal and Hypotheses

As stated in Chapter 1, *“one goal of this work was to develop a flexible mobile computing solution with reasonable investment costs which supports the order picker in a high density pick environment with multiple orders. Compared to text-based pick lists, this solution should reach a higher overall performance with regard to accuracy, speed and usability.”* This goal has been clearly achieved. Pick-by-HMD and pick-by-tablet are both less expensive and more flexible than pick-by-light and both outperform picking with a paper pick list with regards to speed and accuracy. The in-laboratory study, discussed in Chapter 5, showed better usability for pick-by-HMD compared to picking with paper pick lists. While the hypotheses did not make any statements regarding the performance in comparison to a pick-by-light setup, I want to mention that the industrial study at Daimler (with experienced workers) revealed poor user acceptance for pick-by-HMD in comparison to the normally used pick-by-light setup. In this study, pick-by-tablet showed much better user acceptance, comparable to pick-by-light.

The primary hypothesis also stated that a graphical HUD will not only outperform picking with a paper pick list but also pick-by-voice in a high density picking environment. We compared pick-by-HMD against pick-by-voice in the study discussed in Chapter 5. In these results, pick-by-HMD was significantly faster (44.33 vs. 71.03 seconds) and subjective usability was significantly better. Furthermore, the total error rate of pick-by-voice was about 2.5 times higher than for pick-by-HMD (without being significant due to the combination of low error rates, low number of participants and the Bonferroni-correction for multiple comparisons). Thus, for the given setup with a high density picking environment, pick-by-HMD clearly outperformed pick-by-voice. However, I want to highlight that I expect that a pick-by-voice solution would get closer to the performance of pick-by-HMD or pick-by-tablet in low density picking environments.

One of the secondary hypotheses also stated that a graphical representation of what to pick (and where to put) would be interpreted much faster than reading or hearing and interpreting the corresponding text of what to pick (and where to put). The following observations and thoughts support this hypothesis:

- In the study discussed in Chapter 5, just playing all audio instructions necessary (without any break) for a task took longer than the average time needed by pick-by-HMD to complete a task.
- If we compare the information needed to be comprehended and the required input by a user in a high density picking environment between pick-by-voice, a text-based pick list, and pick-by-HMD (like in study discussed in Chapter 5, see Figure 37), it seems quite obvious that pick-by-voice needs more time (hearing, understanding and confirming six audio commands) compared to pick-by-HMD where just one graphic needs to be “*read*”, interpreted, and confirmed. While I would also tend to say that it is reasonable that “*reading*” and interpreting the graphical pick chart is faster than reading and interpreting the text-based pick list, a clearer proof for this claim can be derived from the fact that we also tried a graphical paper pick list which used

the same graphical pick charts as pick-by-HMD. The average task duration was about 13 seconds faster with the graphical paper pick list than with the text-based pick list (51.07 vs. 64.03 seconds).

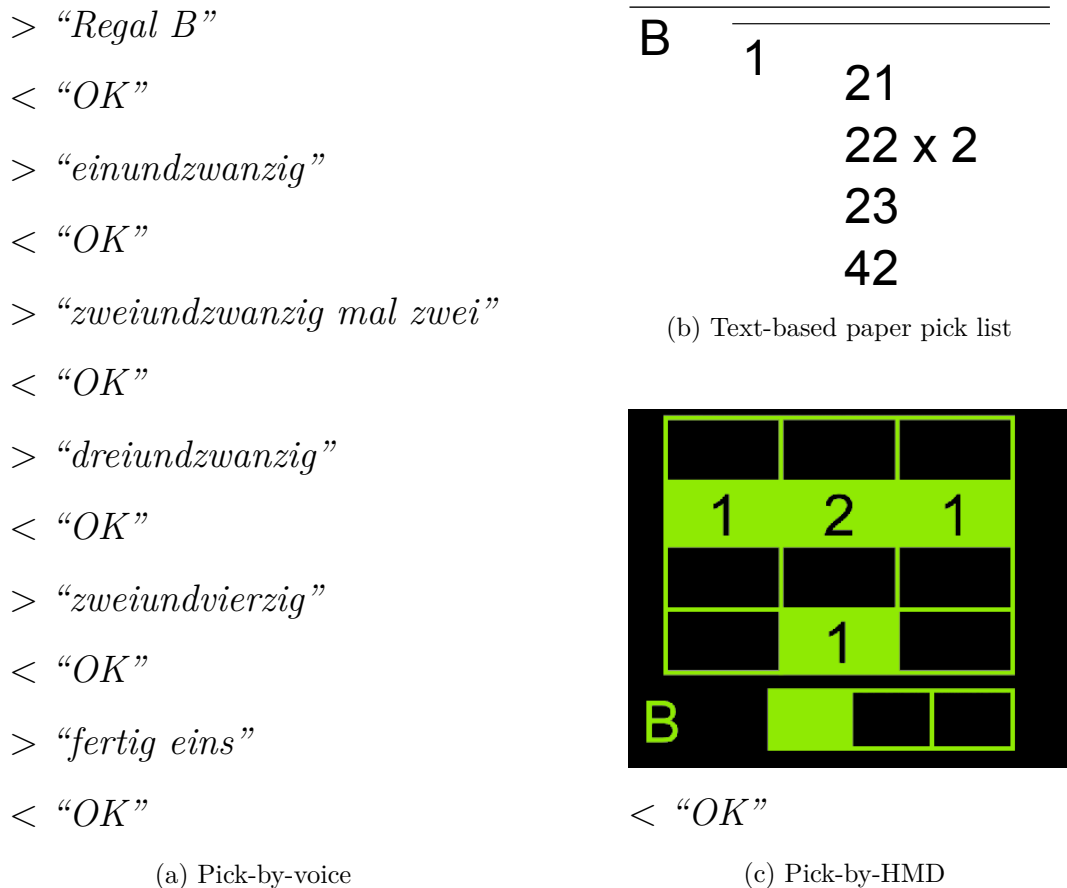


Figure 37: Comparison of the information presented to the user and the required input by a user (“>” indicates audio output; “<” indicates required user feedback (spoken))

Another secondary hypothesis stated that, in contrast to a paper pick list, a HUD is always just a glance away and both hands can be used for picking, improving the picking speed. This hypothesis is supported by the fact that the same graphical pick chart on a HUD (HMD) was significantly faster than on the paper pick list.

The secondary hypothesis that, in contrast to a paper pick list, a mobile computing solution allows for interaction and a context sensitive visualization reduces the risks for errors, is supported by the fact that the study discussed in Chapter 5

showed significantly fewer errors for pick-by-HMD compared to a text-based pick list (less than 1/4 of the errors) but also less than 1/3 of the errors compared to a graphical paper pick list. As this study did not use any pick-detection, I primarily associate this reduction in errors to the fact that with paper pick lists subjects often get confused, losing their place on the list between the steps. On the other hand, the mobile computing solution always shows the current step in a task, avoiding this problem. Also, in the Daimler study much fewer errors occurred with pick-by-HMD and pick-by-tablet compared to a text-based paper pick list. Additionally, the study discussed in Section 4.2 and the *Context Experiment* discussed in Section 6.3 both showed that pick-detection tends to further reduce the total error rate and in both studies “*context mistakes*” were reduced significantly.

8.3 Benefit-Cost Ratio

This section considers investment and operating costs as well as the performance of the pick-chart-based solution. The goal is to show the benefits and thus the potential scenarios, from a business point of view, as to where the pick-chart-based solution (pick-by-tablet or pick-by-HMD) could be used in preference to other methods like paper pick lists, pick-by-voice or pick-by-light. A few of the paragraphs below are from the short paper “*Mobile Order Picking using Pick Charts: Industrial Usage and Future Work*” [6] (I was the only author) presented at the *Workshop on Wearable Systems for Industrial Augmented Reality Applications* (accompanying the ISWC 2012 conference).

8.3.1 Investment Costs

The pick-chart-based approach requires higher investment costs than paper pick lists and similar, probably slightly higher, investments compared to pick-by-voice, while being much less expensive and also more flexible than pick-by-light. Picking zones can be of any size without increasing the investment costs for pick-by-tablet or pick-by-HMD (assuming that the shelves are already available). In contrast, for pick-by-light the investment costs will increase with every shelf and with every pick

location. Below, I give hardware cost estimates for pick-by-tablet, pick-by-HMD, and optional extensions (put-detection and put-to-light).

Pick-by-tablet The market offers many different rugged devices including Android¹ and Windows devices². Depending on the requirements, and batteries for continuous operation, pricing should be between 1400 to 4000 USD.

Pick-by-HMD The MicroOptical SV-6 HMD used in the studies is not sold anymore. In my opinion, the strength of the MicroOptical SV-6 is its light weight, the ability to wear it outside of the normal line of sight, and the small amount of the vision that is obscured. Currently, I was not able to find a commercially available HMD with similar characteristics. Potential alternatives might be the Intevac I-PORT EX 3 (without computing unit, currently sold for about 3500 USD) or the Kopin Golden-i (included computing unit, currently only sold as Developer Kit for 2500 USD). See-through alternatives include the Lumus PD-18 (without computing unit) and the NEC Tele Scouter (included computing unit, currently only sold in Japan for about 5000 USD).

Including the costs for a wearable computing unit and a battery solution for continuous operation, a wearable computer with a HMD currently will range between 2500 USD and 8000 USD. However, many new HMD concepts, prototypes and product announcements have been shown, such as the DoCoMo AR Walker (Olympus MEG4.0), the Laster Pro Mobile Display the Lumus Optical Engine Modules, and the Wearable Display Development Kit or the Google Project Glass³. Also a lower price for the final Golden-i unit is projected, so there is hope for better and less expensive alternatives in the future.

¹Panasonic Toughpad FZ-A1

²Exemplarily, I list four companies offering industrial-grade Tablet PCs with Windows operating systems: Motion Computing, Panasonic, teXXmo and Xplore Technologies.

³Pre-orders for developer units have been available to Google I/O attendees for 1500 USD and should be shipped in 2013.

Put-detection To increase the performance even more, I suggest using a put-detection for the pick cart as evaluated in the industrial study. A put-detection reduces the possibility of placing an item into the wrong order bin. Additionally, it allows an automatic transition to the next pick step improving usability and speed without increasing the investment costs significantly. To include a put-detection system, I expect about a 100-150 USD cost per order bin for a photoelectric proximity sensor plus 100 USD for a corresponding electric control system or 1500 USD if a LRF is used to cover all order bins at once.

Put-to-Light Although not evaluated yet, it stands to reason that put-to-light displays on the pick cart will help the worker find the correct order bins even more quickly and reliably, when many orders are performed and sorted at once. With pick-by-tablet such displays could be directly controlled from the tablet PC by a serial interface, resulting in only slightly increased investment costs. Together with the help of my colleague Hendrik Iben and a student apprentice, we built a prototypical put-to-light solution (see Figure 38) that was directly controlled from a tablet PC (running our picking-client) by a serial interface using BV4513 displays from ByVac. The electronic hardware costs have been less than 20 USD per display and for a final solution – also incorporating an LED, a button and a rugged housing – I would expect additional costs of about 50 USD per order bin.

8.3.2 Operating Costs

Compared to pick-by-light, a benefit of the pick-chart-based solution is its flexibility modifying the setup. If we expect alterations of the shelves and pick locations during operation, this ability gives the pick-chart-based solution a huge benefit regarding operating costs. For example, if a picking zone needs to be extended with new pick locations (by making pick locations smaller) for the pick-chart-based solution, only a configuration of the setup file for the shelves is needed. For pick-by-light, old units would need to be rearranged, and new pick-by-light units must be bought and installed.

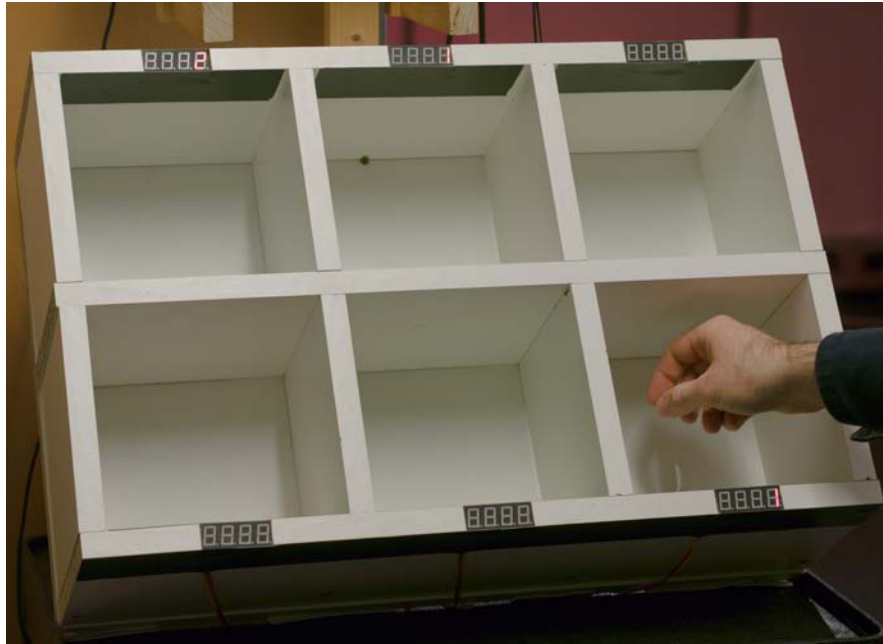


Figure 38: Pick cart with Put-to-light prototype

For the pick-chart-based solution the following operation costs have to be considered:

- A small amount of electric power for charging batteries,
- Replacement batteries after about 300 to 1000 cycles,
- New hardware or repairing when necessary.

As I expect a rugged tablet to survive some years, the operating costs of pick-by-tablet should be very low comparable to pick-by-voice and – if pick lists are not needed – probably cheaper than paper pick lists (due to the printing costs of the paper pick lists).

The operating costs of pick-by-HMD will depend on the lifespan of the HMD, which depends on the design of the HMD and on how carefully workers use the HMD. Thus, it might be comparable to pick-by-tablet or much higher if the used HMD tends to break more quickly.

8.3.3 Performance

Accuracy Compared to paper pick lists or pick-by-voice, all our studies (using high density picking environments with batch picking) showed very low error

rates for the pick-chart-based solution. Paper pick lists and pick-by-voice, however, have been optimized on speed. I expect if pick-by-voice is optimized for accuracy (for example with a required check value to verify for the correct location), lower error rates will be achieved, but with the result of even slower speeds. In comparison to a pick-by-light setup also using put-to-light units, I expect pick-by-tablet and pick-by-HMD to reach similar error rates.

In low density picking environments (and especially if just one order is performed at once), lower error rates can be expected for paper pick lists. Therefore, I expect the benefit with respect to the error rate when updating from a text-based paper pick list to a pick-chart-based solution to be less than in high density picking environments. In low density picking environments pick-by-voice should be optimized for errors and thus, I would not expect an advantage regarding the accuracy in this scenario for pick-by-HMD or pick-by-tablet.

Speed All our studies showed (using high density picking environments with batch picking) HMD picking speeds as being significantly faster than paper pick lists and pick-by-voice. The latest study even showed that – after some practice – the speed of the pick-chart-based solutions is similar to (though probably a little behind) a pick-by-light setup also using put-to-light units.

I am convinced that a benefit of the graphical pick chart, compared with a text-based form or pick-by-voice, is that multiple locations within a shelf or the pick cart can be interpreted very quickly. That means that if there are just a few items to be picked and placed within a pick step, this benefit is reduced or is lost. While there might be still a benefit in time needed for interpretation if just one item is to be picked from a shelf and placed into just one order-bin, the more the user has to walk between the pick steps the more this benefit is negated. To improve the speed in low density picking environments, other optimizations like batch picking should be introduced to achieve a high density picking environment and therefore a higher picking speed.

Usability & User Acceptance In the study discussed in Chapter 5, the subjective usability for pick-by-HMD was significantly better than for paper pick lists or pick-by-voice. However, in the Daimler study where workers usually work with pick-by-light, the initial user acceptance regarding pick-by-HMD was very poor. However, picking with paper pick lists also had very bad user acceptance. If we had introduced pick-by-HMD in a picking zone where paper pick lists were being used, user acceptance might have been better. Pick-by-tablet, in contrast, showed a much better user acceptance in that study, similar to the user acceptance of the normally used pick-by-light setup.

In the in-lab studies I noticed that subjects liked pick-by-HMD because they recognized that it allows them to achieve a high speed and a low error rate – much better than paper pick lists or pick-by-voice. Thus, if in a low density picking environment this benefit is reduced, this might also have a negative effect on the usability and user acceptance of pick-by-HMD (especially if the discomfort of wearing a computer with a HMD might then seem not worth the benefit).

8.3.4 Conclusion

In high density picking environments, I expect pick-by-tablet to show a significant improvement in performance compared to paper pick lists or pick-by-voice. In the industrial study the performance of pick-by-tablet was close to the performance of a pick-by-light setup with put-to-light units. Investment and operating costs of pick-by-tablet are relatively low, comparable to pick-by-voice while being much lower than for pick-by-light – especially in picking zones with many pick locations. While pick-by-HMD would also reach an accuracy and speed similar to pick-by-tablet, I recommend not to introduce it for industrial usage yet, as the hardware and user acceptance will need further investigations. Nevertheless, we see potential for pick-by-HMD. A case study with a HMD might be of high interest in a scenario where a tablet PC or mobile display is not appropriate (for example if there is not enough space to move a pick cart in front of the shelves). Also the HMD has the advantage that the HMD is always just a short glimpse away, while a tablet-PC on

the pick cart – standing in front of a shelf – will require to turn the head towards the pick cart. For this reason pick-by-HMD might even show a better performance than pick-by-tablet after a longer training phase.

Only a small improvement in errors and speed can be expected in low density picking environments when switching from paper pick lists or pick-by-voice to a pick-chart-based solution (less complexity in the picking environment already results in few errors and walking to each shelf is the largest expenditure of time). As the pick-chart-based solutions can handle much more complex pick tasks with very low error rates, picking density can be increased by changing from single order picking to batch picking (or increasing the number of orders performed at once) when feasible. As a result, pick-by-tablet will achieve a higher speed while maintaining or even improving the error rate.

8.4 Further Observations and Lessons Learned

8.4.1 HMD characteristics for pick-by-HMD

HMDs can be categorized into monocular or binocular and look-around or see-through classes [35]. Experiments where different HMD configurations were compared showed a better performance for monocular HMDs than for the binocular HMDs [35, 39]. Typical binocular HMDs obscure much of the worker’s field of vision; thus we only considered monocular HMDs.

So as not to obscure the perception of the environment during the primary task of picking and placing the items, an unintrusive display and the ability to wear the HMD eyepiece outside of the normal line of sight are of high importance. In our first study, as discussed in the introduction, we used a Trivisio M3 color see-through HMD. Within this study I mentioned that with this see-through HMD the perception of the environment is much worse than with the MicroOptical SV-6 look-around HMD. The perception of the environment through the see-through area of the HMD is limited, and the housing of the HMD eyepiece obscures much of the field of vision. The MicroOptical SV-6 HMD, in contrast, has a smaller field

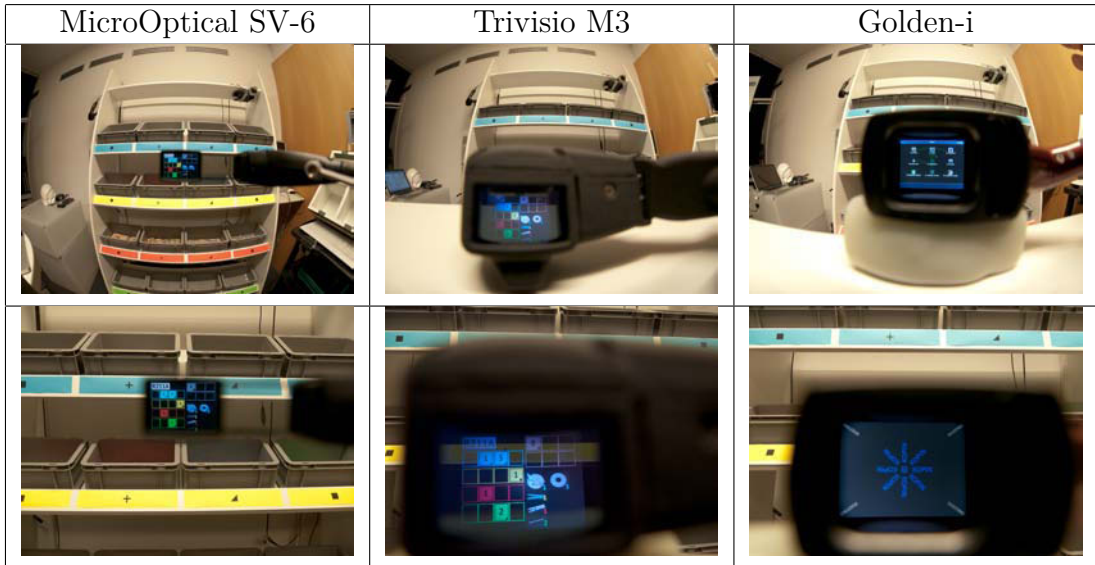


Table 8: Comparison of the field of view of the virtual screen sizes of different HMDs and their occlusion of the field of vision. The images of the first line are shot with a fish-eye lens with a diagonal field of view of nearly 180° . The second line with a lens with a diagonal field of view of approximately 75° .

of view, and the housing of the HMD eyepiece only obscures a very small part of the field of vision. Thus, if the SV-6 eyepiece is positioned outside the normal line of sight, the worker can glance at the HMD without being distracted when he is not required to look at the HMD. Table 8 shows some photographs taken through three different HMDs to demonstrate the field of view and the occlusion of the field of vision. Figure 39 shows that the SV-6 can be easily positioned out of the normal line of sight, allowing a good view of the environment.



Figure 39: The MicroOptical SV-6 can be positioned outside of the normal line of sight. Note that the field of view of the camera lens is nearly 180° (in the diagonal), which is higher than the field of vision of a human.

Another drawback with the M3 HMD was that visual interference can occur under some conditions. When looking in the direction of inhomogeneous background (environment) – especially when the environment was bright and while walking or moving your head around – the HMD can be more difficult and strenuous to read as your eye sees both the moving background (environment) and the virtual screen at once. A look-around HMD, in contrast, blocks the light in the field-of-view of the virtual screen so that reading from the HMD becomes much easier – especially in bright environments with inhomogeneous backgrounds (see Figure 40). Thus, in our scenario where we do not use augmented reality, a look-around HMD (with a small occlusion of the field of vision) might be a better choice.⁴ The results of Laramee and Ware [35] support this assumption with their study focusing on binocular rivalry and visual interference effects between an opaque and a transparent HMD. With a dynamic background, visual interference for the see-through HMD was highly significant (comparing an opaque HMD vs. a transparent HMD), resulting in an increased response time of 43%.

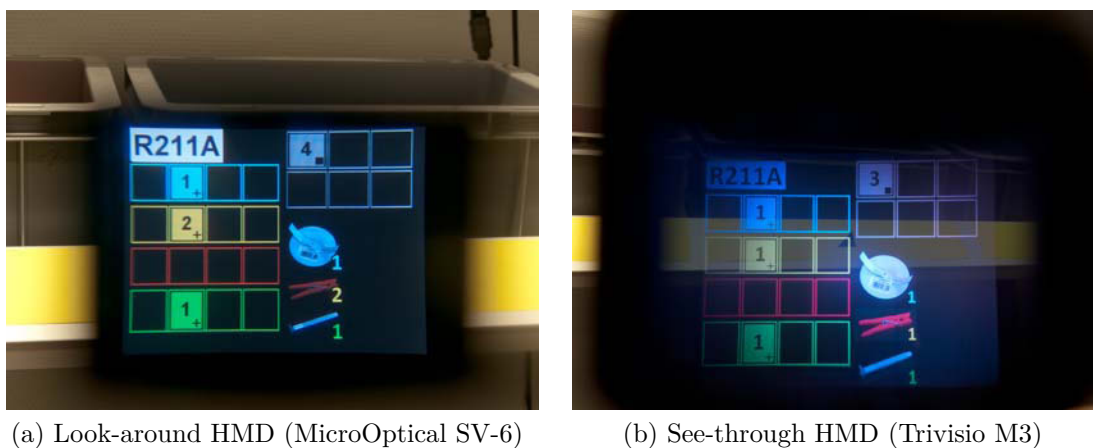


Figure 40: Look-around and see-through HMD in comparison (images are shot under same environmental lighting and with same exposure). Please note that the brightness of the environmental lighting has an impact on the readability of a see-through HMD. Head movements produce a moving background within the see-through HMD, which makes reading the see-through HMD more difficult.

Obviously, a HMD also has characteristics such as resolution, brightness and

⁴A brighter see-through HMD might compensate for the problem of seeing the environment through the screen.

contrast. For typical wearable user-interfaces and environments, the brightness and contrast of look-around HMDs are seldom problematic, and for pick-by-HMD, a resolution of 640x480 like offered by the MicroOptical SV-6 proved to be sufficient. However, during the studies I learned that a HMD has other characteristics that are more important (when used for pick-by-HMD).

Of special importance for workers wearing corrective spectacles is the physical eye relief. The eye relief is defined as the distance from the plane of the last physical element of an eyepiece to the exit pupil of the user's eye [56, p. 114] at which the user's eye can obtain the full viewing angle [78]. Wearing corrective spectacles myself, I experienced many problems with different HMDs where the eye relief was too short, so that the full content of the HMD screen cannot be seen (see Figure 41d as example for the slightly cropped content of the screen when the HMD eyepiece is placed behind the eye relief). The MicroOptical SV-6 HMD instead has a large physical eye relief leaving a lot of room for corrective spectacles. Figure 41 demonstrates the effect of different distances of the HMD.

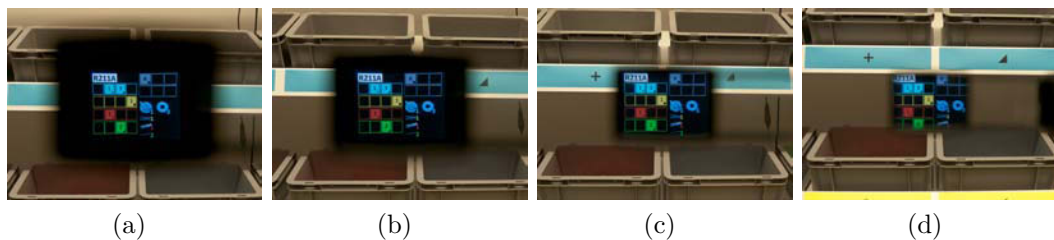


Figure 41: Simulating different distances (with increasing distances from left to right) between the SV-6 eyepiece and the eye. In (a) the SV-6 is positioned very close to the eye with the effect that the eyepiece obscures more of the field of vision than necessary. In (c) the distance between the HMD eyepiece and the eye is approximately set to the eye relief of the HMD. Parts of the screen disappear when positioning the HMD eyepiece even further away from the eye (see (d)). Typically a distance between the ones simulated in (b) and (c) is used when working with the SV-6.

Another characteristic of a HMD is the focus or, in other words, the distance of the virtual screen. Many HMDs have a fixed focus set to a reasonable distance and a few, like the MicroOptical SV-6 or the Golden-i, even offer an adjustable focus. For pick-by-HMD my experience showed that a distance of about an arm-length –






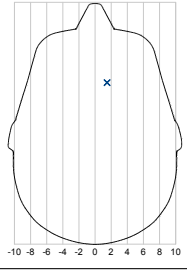
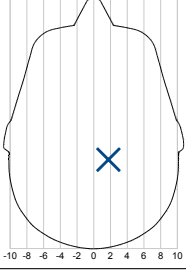
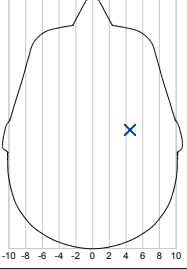
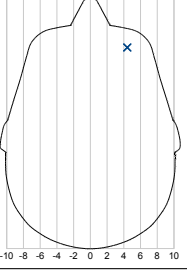
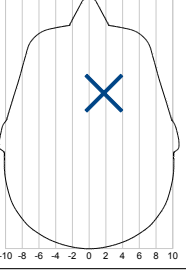
MicroOptical SV-6	Kopin Golden-i	Trivisio M3	Vuzix Tac-Eye LT	Trivisio M3 Cam
				
				
≈77g	≈283g	≈137g	≈92g	≈452g

Table 9: Weight and center of gravity of the HMD eyepieces while being connected to a holder for carrying the eyepiece. (During the measurements the connector cables are held so that their influence on the measurements is small. However, holding the cables causes minor fluctuations.)

about 80cm +/- 20cm – is a reasonable focus distance.⁵ An adjustable focus helps to set a usable focus distance for the preferred HMD eyepiece position, especially for people with bifocal glasses.

Wearing comfort is of very high importance for good user acceptance. Therefore, an important factor is the design of the solution for carrying the HMD eyepiece. A solution that produces heavy pressure marks on the users nose, for example, will reduce the wearing comfort. One objectively measurable factor for the wearing comfort of a HMD is the weight and the center of gravity. We built a device to measure the total weight and the center of gravity (reduced onto a 2-dimensional plane) of a HMD eyepiece (including its holder) by measuring the weight distribution on three defined measuring points. Table 9 shows the measured results of five different HMDs. Below, I state my own subjective perception of the wearing comfort of these HMDs and a short interpretation of the measured

⁵My experience has shown that users that are inexperienced with HMDs find it easier to focus on shorter distances like 60cm or even less (probably because they expect to look at a screen very close) but that more experienced HMD users realize that a longer focus distance of 80cm-1m is less strenuous for the eye.

results. Further investigations would be required to objectively understand the correlation between the experienced wearing comfort and the actual weight and center of gravity.

MicroOptical SV-6 I added a counterweight of approximately 20g to the SV-6 holder (as used in the industrial study) on the left side. In spite of the increased weight, the measured weight is still quite low at 77g, and the wearing comfort is improved, as the center of gravity with the counterweight closely matches the center of the x-axis. The SV-6 is a little front-heavy, but due to the low weight of 77g this is not a big issue.

Kopin Golden-i The weight of the wireless Golden-i – including the battery and computing unit – is much higher, but its center of gravity is close to the optimal position, and therefore feels very comfortable to wear with regard to its weight and center of gravity.

Trivisio M3 The center of gravity of the M3 is on the right side. It is noticeable but acceptable due to the weight of 137g.

Vuzix Tac-Eye LT The center of gravity of the Tac-Eye LT is far off the center to the front and right. As result the 92g of this HMD feels heavy and unbalanced.

Trivisio M3 Cam The combination of being front- (and a little right-) heavy and having a weight of 452g makes this HMD (in my opinion) the most uncomfortable to wear of the HMDs shown in this table.

Ruggedness is of high importance for industrial usage. The experience of our wearable computing workgroup (owning many MicroOptical SV-6 and other HMDs) was that the most critical parts of the HMDs are the cables, which often get defective after extended usage. From this point of view a solution like the

Golden-i – which represents a complete wearable computer without any cables – is favorable. Additionally, a design like the Golden-i does not require a wired connection to a separate computing unit, which increases the handling and wearing comfort and overall user acceptance.

Concluding, my preference would be something like an improved Golden-i with a better means of conducting away heat from the computing unit, less shaking of the eyepiece during movement, and a smaller eyepiece (optics) similar to the Micro Optical SV-6 using a modern (and size compatible) micro-display like the Sony ECX331A [67] or Epson’s ULTIMICRON L3F04S-8x [21] (as used in leading electronic viewfinders in the mirrorless interchangeable-lens cameras Sony NEX-7 and Olympus OM-D E-M5).

8.4.2 Field-of-View, Resolution and Human Acuity with the SV-6

I measured a field of view of about 18° for the SV-6, and I experienced that this field of view is sufficient for people with normal vision (normal acuity at the focal distance of the SV-6) to quickly perceive the required information. A benefit of the small field of view is that while looking on the HMD screen, the blind spot does not obscure any information that is shown on the screen even while focusing the right side of the screen (see Figure 42).

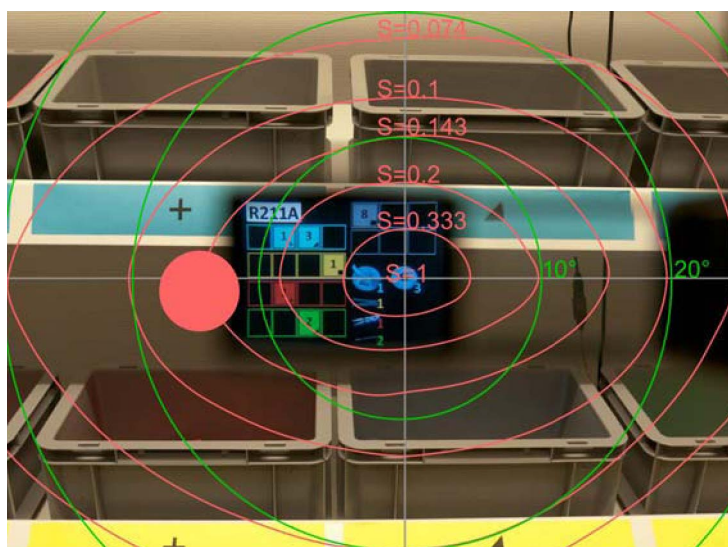


Figure 42: MicroOptical SV-6 with a field of view of about 18° showing an overlay of the square-wave grating acuity and blind spot results by Theodor Wertheim

A human with normal vision can read the Snellen letter with a height of 5 arc minutes (a typical distance for this test is 6m (about 20 feet) with a Snellen letter being 8.7mm tall) [56, p. 257]. With a height of 5 arc minutes the smallest gap that a person needs to resolve between the strokes of the Snellen letter is 1 arc minute (see Figure 43). Assuming a human with normal vision and the same

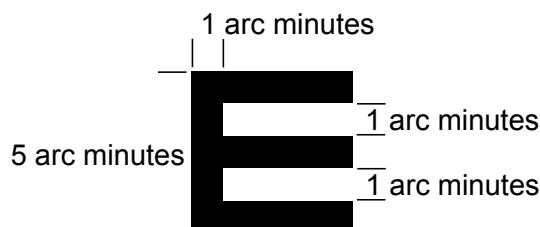


Figure 43: Dimensions of Snellen acuity letter which a human with normal vision can read

acuity at closer distances (same cycles per degree), a Snellen letter in the smallest possible representation of 5x5 pixel, on a HMD should be resolvable, if a pixel has a size of at least 1 arc minute.⁶ The MicroOptical SV-6 with a field of view of 18° has a pixel pitch of about 1.35 arc minutes. The biggest area that a user might try to perceive at once on the pick-by-HMD user interface is probably the area representing the actual shelf. In the industrial study, the diagonal of this shelf representation corresponds to about 10.4°. Assuming a fixation on the middle of the shelf representation, the corners of this representation would be about 5.2° from the center. Using the formula for acuity falloff (with acuity normalized to 1 in the fovea) [28]

$$A(e) = \frac{2.5}{e + 2.5} \quad e = \text{degrees from fovea}$$

at 5.2° the acuity should be 0.325 relative to the acuity at the fovea. Thus, at 5.2° a person with normal vision should be able to resolve a detail of about 3.08 (1/0.325) arc minutes, which corresponds to about 2.28x2.28 pixel on the

⁶To confirm, I tested 3 subjects, determining the acuity of their right eyes at near distances by asking them in which orientation a randomly rotated Snellen letter (5x5 pixel with a pixel pitch of about 0.223mm) was shown. The furthest distances the subjects were able to resolve the Snellen letter ranged from 0.75m – 1.4m corresponding to a minimum angle of resolution between 0.55 and about 1 arc minutes. These values correspond to about 30 – 55 cycles per degree which is in the range of normal – excellent vision [56, p. 259].

SV-6 (the ratio between the angle of a SV-6 pixel height (1.35 arc minutes) and the calculated acuity at 5.2° (3.08 arc minutes)). Thus, by scaling the 600x480 image down with a factor of 1/2.28 (using a Gaussian filter⁷ for calculating the individual pixel intensities) and then back to its original size, we can roughly simulate the acuity a person with normal acuity would have at the corners of the shelf representation (see Figure 44). Obviously, in the figure even the small

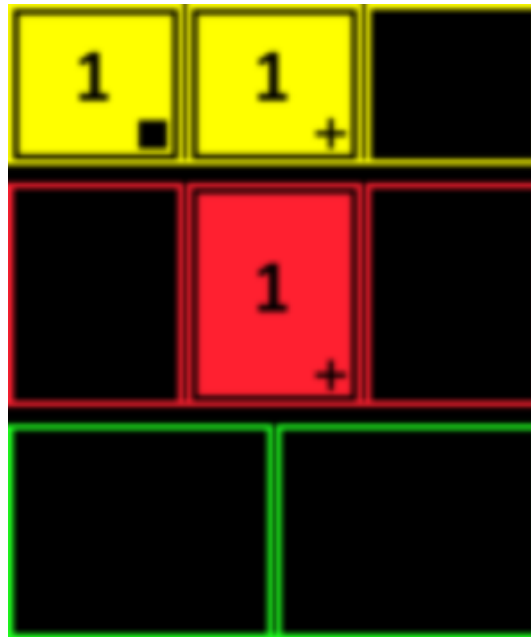


Figure 44: This image roughly simulates the acuity a human with normal vision would have at the four edges of the shelf representation when fixating on the center of the shelf representation while using the MicroOptical SV-6 (Image was scaled down and back to its original size with XnView using the “Gaussian” setting)

symbols are well resolvable, which means that all the available information from the shelf representation should be recognizable while the user’s eye fixates at the center of the shelf representation.

8.4.3 Becoming Accustomed to Using a HMD

Becoming accustomed to using a HMD takes some time. The required time depends not only on the HMD but also on the user. Some subjects can read from a specific HMD quite well right from the beginning and improve quickly as they

⁷The low-pass binomial filter with kernel [1 4 6 4 1] mentioned by Tilke et al. [28] is a 5x5 Gaussian filter, and the procedure described there for modeling reduced acuity shows comparable results for an acuity of 0.5.

learn to focus the HMD. Other subjects have more problems at the beginning and improve more slowly. From my own HMD experiences and observations during the studies with “HMD-novices”, I expect that the following issues are the most relevant to users’ accommodating to a HMD.

Focusing on the virtually distanced screen while the HMD eyepiece is close to the eye I think many people unconsciously try to focus on a close object. In my own experience, I can state that after getting used to the Micro Optical SV-6 (with an adjustable focus from about 2 to 15 feet, or 0.6 to 4.6m), I set the focus a little more distant than when I started using the HMD (where I set the HMD to the closest focus possible).

Binocular rivalry The SV-6 screen is seen by one eye, but normally we see things with both eyes (within the field of view of binocular vision). Accordingly, some people close the other eye to better read from a HMD in the beginning. It sounds reasonable that this issue might be present more often if the HMD is worn over the non-dominant eye. However, from observations and my own experience also wearing the HMD on the non-dominant eye, I can report that adjusting to binocular rivalry⁸ is normal, independent of the eye on which the HMD is worn.

Adjusting the HMD and finding the preferred spot At the beginning users sometimes find it quite difficult to position the HMD eyepiece in a useful spot with the correct angle so as to be able to read the whole screen. When starting to use a HMD this issue sometimes leads to frustration and an initial reluctance regarding the HMD usage. From my own experience, I can report that with some training you identify your preferred spot and also internalize the correlation of your adjustments on the position and angle of the HMD eyepiece and the corresponding effect on the position and angle of the virtual screen. This learning allows a much faster adjustment of the HMD.

⁸A definition is given in the work of Laramee and Ware [35]

8.4.4 Eye Dominance

It is not certain how eye dominance⁹ will impact performance regarding different scenarios for HMD usage. However, Laramee suggested in his work about rivalry and interference with a HMD that a HMD should be normally worn over the dominant eye [35], and in the work of Rash et al. [57] the non-dominant eye was reported to show worse results. As the majority of humans are right-eye dominant, most of the HMD manufacturers decided to deliver their HMDs configured for the right eye. As the MicroOptical SV-6 can be configured for either eye, in the study discussed in Chapter 5 we used the HMD over the subject's dominant eye. Then, in the pilot tests of the *User-Interface Optimizations* study, we observed that two left-eye dominant subjects focused on the part images when available and not on the pick chart. After this observation we asked the second of these subjects to use the right, non-dominant, eye for the HMD. As this subject stopped focusing on the image, I concluded that the developed user interface is better suited for the right eye. Therefore, since then we asked all subjects to wear the HMD on the right eye independent of the eye dominance. Our observation is consistent to the suggestion of Witt et al. [79], that a user interface for a HMD should be designed, so that the important information is shown on the screen side that is closer to the visual center. As our study did not reveal any significant difference¹⁰ and the images on the HMD should just be used for a final check and not for finding the location of the item, we continued to use the right eye and not the dominant eye for the HMD.

Further investigations would be of considerable interest. However, I expect the results to be dependent on the task (e.g. how long and how often you have to look at the HMD). Further factors like the HMD characteristics (especially see-through vs. look-around, but also the field of view of the HMD and the amount of the field

⁹A definition is given in the work of Laramee and Ware [35]

¹⁰Like in the work of LaFleur et al. [34] "*Performance data did not reveal any significant eye-dominance effects. Additionally, there were no significant effects on participants' subjective preference between dominant and non-dominant eye for this task.*"

of vision that gets obscured by the HMD) and also the time available for training¹¹ might be of relevance. For example, I could imagine that for an augmented reality task like the “*Pick-by-Vision*” approach proposed from Reif et al. [59], a monocular see-through HMD on the dominant eye might show better performance than on the non-dominant eye, whereas for our proposed pick-by-HMD solution with a look-around HMD the non-dominant eye might be equivalent in performance to the dominant eye.

8.4.5 Planning and Conducting an Industrial Study

Planning and conducting an industrial study in a huge company like Daimler was much more complicated and required much more time than I expected. Originally, I planned to conduct the industrial study at the Daimler plant in Mannheim. The plans for this study started in the second half of 2009 and became very intensive in the first half of 2010 (including visits at the Daimler plant in Mannheim). Many different departments and individuals were involved and obtaining all the required information and allowances, especially regarding the IT-infrastructure, proved to be difficult as it was often unclear who had the required knowledge, was responsible and could give a commitment. Patrick Zschaler from the Daimler Plant in Mannheim and I observed the workers (first by simply observing them and then by using the thinking-aloud method) and asked fixed and open questions regarding the order pick tasks and the context to the running assembly line. We also asked for feedback regarding different user-interface variations. The aim was to

- understand the way workers perform the order pick tasks and understand their thoughts and movements,
- involve them in the project by giving them the ability to give feedback and suggestions regarding the user-interface (participatory design).

¹¹Perhaps more time is needed with the non-dominant eye to get used to reading from the HMD. However, afterwards these users might be able to achieve better performance as the dominant eye can be used to view the environment without interference from the HMD.

In the middle of 2010, the works council (the works council consists of the plant's workers' representatives who are involved in the working conditions and rights of workers) objected to our plans to perform the study at Daimler in Mannheim.

In August of 2010, I contacted an employee of Daimler in Bremen (responsible for new order picking technologies) regarding an industrial study. With his help, getting in contact with the necessary individuals was easier. However, the financing of the study was unresolved for a long time, and a high workload in the plant made the planning of the study very difficult. For some time there was the risk of another failure. Just in time, the financing was resolved and a picking zone found where the study could take place. Due to the very short time that remained and the high workload in the plant we did not have the chance to get in contact with the workers in advance and could not involve the workers as we did when we prepared the study in Mannheim.

About one year after the initial contact with Daimler in Bremen the study started. Sadly, most workers were highly skeptical about us and the pick-by-HMD approach (also see Chapter 7), and many workers refused to participate.¹² Fortunately, after some days the skepticism against us lessened, and some workers agreed to give pick-by-HMD a try.

As I already stated in Chapter 7, we learned that we underestimated the reluctance of the workers regarding new technologies like HMDs, the effect of group dynamics between the workers (influencing each other by loudly denigrating the wearable computer's appearance and other aspects), and the resulting effects on the study. This experience underscores the importance of establishing a plan (including social-psychological aspects) on how to introduce a new technology to a current process. Reporting from their experiences with augmented reality projects in industrial applications, Regenbrecht, Baratoff, and Wilke come to a

¹²One reason for the increased skepticism and reluctance is that workers were sensitive to possible negative effects (like reduced number of workers, a faster expected work pace, and higher workload) such a new technology might bring.

similar conclusion with their statement that key persons in innovator roles are needed [58]. *“These people should work as closely as possible with the researcher, know the application field well, and be widely accepted among their colleagues to serve as a point of multiplication for later dissemination. If a project does not have such a person who fully accepts the approach and is willing and able to drive it to success, the entire project will probably fail. Furthermore, the integration of many parties in the early process of the project (managers, company physician, union representatives, and so on) is laborious but worthwhile. Additionally, usability studies with representative subjects should be a part of every application project.”*

I think this statement generally applies to industrial studies using HMDs in a similar (but maybe a little less intensive) way. An executive at Daimler supported the evaluation of the pick-by-HMD approach, but he was not involved in the group dynamics of the workers who participated in the study. While this situation did not lead to a complete failure of the study, it at least influenced the first days of the study, as the workers did not trust the pick-by-HMD solution.

Chapter IX

RECOMMENDATIONS FOR FUTURE WORK

There are still many possibilities for future work. In the following sections I name some of them, grouping them into *Software and Hardware Developments*, *Controlled Studies*, and *Industrial Case Studies*.

9.1 Software and Hardware Developments

While the graphical pick chart – including different visual extensions – proved to show very good results, there are still possibilities for further improvements regarding the whole solution. The following list shows a few examples.

- Implementation of speech prompts for shelf changes.
- Visualization of picking context such as the remaining number of pick steps.
- Development and evaluation of a “*smart*” pick cart that can be used with the graphical pick-chart-based solution. The pick cart should offer put-detection and put-to-light displays. It could sense its location for plausibility and offer check-weighing for detecting wrong items or a wrong number of items.
- Miniaturization of the wearable computer for pick-by-HMD or a wrist-worn device by porting our pick-chart-based solution to Android, Windows CE or similar devices. A very small and lightweight Android device for porting could be Google Glass.

From these I would start with the ones that can be realized with acceptable investigations and which I expect to have the best benefit-cost ratio, namely speech prompts for shelf changes, a pick cart with a put-detection and put-to-light displays; and for studies investigating HMDs or wrist-worn devices a miniaturization

of the wearable computer. A small study could ensure that these developments do not negatively effect the pick-chart-based approach.

9.2 *Controlled Studies*

We only evaluated the pick-chart-based solution in combination with the Micro-Optical SV-6 HMD in controlled and quantitative studies. We also tested a tablet-PC in the industrial study, but we have not been able to gather quantitative performance measurements. Hence, it would be of interest to compare the graphical pick-chart-based solution on different kind of devices (tablet-PC, wrist-worn device, different types of HMDs) to traditional paper pick lists, pick-by-voice, pick-by-light and other newly developed picking solutions such as the augmented reality pick-by-vision system described by Reif et al. [59] or the augmented reality solution offered by KNAPP [29].

The industrial study supports, in particular, my assumption that at least a few days are necessary to adapt to a HMD and in Section 8.4.3, I discussed the reasons that I expect play an important role. I also expect that feeling comfortable in using a HMD over whole working shifts requires more time for adapting than the time required to be able to use a HMD with high performance. The role of eye dominance would also be of interest for an evaluation (see Section 8.4.4). Thus, a controlled study that evaluates the learning curve, the adaption over a longer period, and the role of eye dominance would be of high interest. Such a study could focus on the picking scenario with our approach. A more comprehensive project could evaluate these issues in general for different scenarios and HMD classes.

A more concrete suggestion regarding our picking scenario is a study that considers the learning effects of novices over three weeks¹ for the following six modalities: pick-chart-based pick-by-tablet, pick-by-HMD (with both: dominant and non-dominant eye (left and right eye)), and wrist-worn device, benchmarking

¹In the industrial study after one and a half week of pick-by-HMD usage we observed a much better adaption to the HMD by the participant using the HMD over three weeks.

against traditional paper pick lists and pick-by-light. From the experiences of the previous studies I would suggest 20 subjects that should participate over 3 weeks, 5 days a week, with 6 hours each day.² Such a study would be very challenging with 1920 hours of subjects participating, making a founding and realization unlikely.

A more likely realization could be two independent studies. A first study could focus on comparing the pick-chart-based solution with a tablet-PC to an wrist-worn device, benchmarking against traditional paper pick lists and pick-by-light (not considering learning effects over a longer period).³ Afterwards, the second study could compare our pick-chart-based solution on a tablet-PC (or wrist-worn device in case it would show a higher performance than a tablet-PC in the previous study) to pick-by-HMD (with the HMD worn on the right and left eye to evaluate the role of eye dominance and other potential performance differences dependent of the eye) in a study also considering learning effects of novices over three weeks.⁴

9.3 Industrial Case Studies

I believe that the previous studies proved that our pick-chart-based solution is ready to be evaluated in industrial case studies. A first case study could evaluate the use of pick-by-tablet in a picking zone where currently paper pick lists are used, but where a pick cart with multiple orders can be accommodated. Such a case study would give the possibility to evaluate the improvements of the pick-chart-based pick-by-tablet operation compared to an operation with paper pick lists in real industrial environments. After a successful outcome of this case study the solution could be prepared for extensive use in different order picking scenarios to evaluate the role of the number of parallel orders, the shelf sizes, the number of boxes per shelf, picking density, and the items quantities and sizes.

²Including some small breaks resulting in a little less than one hour per modality in the first two weeks, and in the third week just one modality per day over six hours.

³I would limit the duration between three and five hours per participant, with 16 - 20 participants in total resulting in 48 - 100 hours of subjects participating.

⁴This study could be conducted with just 12 participants to reduce the required extent, resulting in 540 hours of subjects participating (expecting the same amount of time per modality per participant as in the less likely realizable study design mentioned first).

Independent of the previously stated case studies, smaller case studies with single workers could investigate the usage of HMDs for the pick-chart-based solution, to learn about long time user acceptance, performance after longer learning periods, and durability of HMDs in industrial settings. If these case studies show scenarios where a HMD is well accepted by the workers and provides superior performance to pick-by-tablet or wrist-worn devices, bigger case studies might be realized.

Chapter X

CONCLUSION

As stated in Chapter 1, the goal of this thesis was to develop a flexible mobile computing solution with reasonable investment costs which supports the order picker in a high density picking environment with multiple orders. Compared to text-based pick lists, this solution should reach a higher overall performance with respect to accuracy, speed, and usability.

The studies discussed in Chapters 5 – 7 showed that this goal was reached with the pick-chart-based systems, clearly outperforming paper pick lists in terms of accuracy, speed, and usability. The pick chart allowed the user to pick and place the items fast and unerringly.

While the original wearable computing solution with a HMD showed very good performance in terms of speed and accuracy in all studies, the industrial study discussed in Chapter 7 revealed that the user acceptance in an industrial environment for HMDs is problematic; user acceptance for the same user-interface shown on a tablet-PC is much higher. Based on the results and the observations of the studies, I am convinced that pick-by-tablet could be used beneficially at many picking scenarios. In environments where a high picking density exists (or can be achieved, for example by changing from single order picking to batch picking), I expect pick-by-tablet to show a significant improvement in performance compared to paper pick lists or pick-by-voice. Pick-by-HMD, however, could still make sense in scenarios where pick-by-tablet is not appropriate. Further studies might also reveal that after a longer training phase the speed and accuracy of pick-by-HMD is superior to pick-by-tablet. I am also optimistic that the user acceptance problem can be overcome with improved HMDs and smaller computing units – like Google Glass – and a more slow and gentle introduction of pick-by-HMD.

Appendix A

STATEMENT OF MY OWN CONTRIBUTIONS AND CONTRIBUTIONS OF OTHERS

A.1 Development of User-Interface

My contributions to the design and development of the user-interface – which we called *Picking-Client*, started with the study discussed in Chapter 5. Therefore, I used pre-existing code and the software architecture from the previous pilot tests and the study of Iben et al. [27] (with myself as second author). Since then all the design and development of the *Picking-Client* (and also for the other tested modalities like the voice (see the study discussed in 5) or paper-based versions (see the studies discussed in Chapter 5 and 7)) have been my contributions.

A.2 Other developments

My colleague Hendrik Iben continued the development of the middleware. This work includes the middleware that was responsible to submit the pick tasks to the *Picking-Client*, the *ContextServer* and *ContextClient* (which was used to exchange messages between the different applications like the pick-detection and the *Picking-Client*¹), and the *SafeLogContextProvider* (which was used to send the pick- and put-detections of the SafeLog pick-detection to the ContextServer (used in the industrial study)).

Hendrik Iben also wrote the picking detection used in *Context Experiment* of the study discussed in Chapter 6.

Together with Hendrik Iben I also implemented the video annotation tool mentioned in the study discussed in Chapter 5.

¹I made some minor changes to allow a restart of the ContextServer (in case of any technical problem) without the need to restart any application using the ContextClient.

A.3 Studies

The work of Iben et al. [27] (and mentioned in the introduction of this thesis), I helped my colleague Hendrik Iben in planning and conducting the study. While conducting the study we were helped by colleagues of the BIBA and the Hochschule Bremen. The evaluation and the writing of the first version of the corresponding paper was mostly driven by Hendrik Iben and me, with help of Carmen Ruthenbeck (BIBA) and some minor contributions from Tobias Klug (SAP). For the final version of the paper presented at the ICMI 2009 (where I was second author), we were helped by Thad Starner.

The study discussed in Chapter 5 I planned with the help of Thad Starner and Kimberly Weaver from the Georgia Institute of Technology. I was mainly responsible for conducting the study but was helped by Thad Starner, Kimberly Weaver and Hendrik Iben. Kimberly Weaver, Thad Starner and I collaboratively evaluated the results of the study, and Kimberly Weaver helped me to bring our research and our evaluation results to the HCI-community. She did most of the writing for the corresponding paper presented at CHI 2010 (I was second author).

The *User-Interface Optimizations* study was mostly planned and prepared by myself with support or suggestions of Hendrik Iben, Anna Lewandowski (SAP), Jörg Rett (SAP) and Patrick Zschaler (Daimler AG). The experiment was mostly driven by myself and Hendrik Iben with support of Stephan Gitz (Hochschule Bremen), Patrick Zschaler (Daimler AG), Ali Safdar and Anna Lewandowski (SAP). I performed the evaluation together with Hendrik Iben and Anna Lewandowski. The first version of the paper was mostly written by myself with support of Hendrik Iben, Anna Lewandowski and Patrick Zschaler. Thad Starner helped me to improve the writing, and the paper was presented at ICMI 2011 (I was first author).

The industrial study was mostly planned and prepared by myself with some support from Hendrik Iben and Patrick Zschaler. While conducting the study I was supported by Patrick Zschaler and Hendrik Iben. The evaluation was mostly

performed by myself with some help from Patrick Zschaler. The first version of the corresponding paper was written by myself with some minor support from Patrick Zschaler. Thad Starner helped me again in improving the writing for the final paper which was presented at the ISWC 2012 *Workshop on Wearable Systems for Industrial Augmented Reality Applications* (with myself as first author). The poster presented at the ISWC 2012 conference was mainly written by me and Thad Starner with some suggestions coming from Patrick Zschaler (I was first author).

Appendix B

INTERVIEW WITH CHRISTIAN BÜRGY

Christian Bürgy is CEO of teXXmo and organized the *Workshop on Wearable Systems for Industrial Augmented Reality Applications* at the ISWC 2012. Within this context I made a short interview with him on *Wearable Computers in Industry*.

Hannes: Can you give me some information about industrial scenarios that got investigated by the scientific wearable computing community?

Christian: Besides the one you will know from the TZI where inspections of steel cranes were investigated, there have been several at CMU, including the one I was responsible for in cooperation with Bosch. A lot of research also came from MIT – compare work of Steve Mann and Thad Starner.

Hannes: In your Ph.D. you wrote about the projects from the Carnegie Mellon University. Which ones have been most famous and which ones have been your favorite ones?

Christian: I guess the VuMan family of CMU wearable computers have been largely known. Most of these projects were proof-of-concept projects, in which first studies were made and user feedback was collected. Please consider the wearable computer tree of CMU to see all of these efforts. Besides my own, I guess I most liked the system with the rotary dial as one-handed input device. Today, one could say that speech recognition is more advanced and made such UIs (partially) obsolete, but at that time it seemed to be a very good concept.

Hannes: Which of the industrial scenarios seemed to have potentials for industrial usage and which of these scenarios finally got successfully deployed in industry?

Christian: Up to now, mostly inspection-related processes have been investigated.

In broader industrial use, I only know of pick-by-voice systems, which are in fact audio-based wearable computers, or wrist-worn PDAs, which might not be as successful as pick-by-voice, though. Right now, quite a few companies and institutions are working on picking supported by wearable augmented reality systems.

Hannes: And what do you think have been the reasons that other scenarios failed?

Christian: No clear return on investment and a lot of obstacles in user interaction; pick-by-voice does not need a HMD and thus, hardware costs are lower, the system can be quite ruggedized and also user interaction is minimized and thereby, easier to learn and handle.

Hannes: Do you know some successful scenarios that include the use of HMDs?

Christian: I don't have insight in military projects, hence the answer is "no".

Hannes: From Xybernaut for example I found the Bell Canada large-scale market trial, but the trial showed that most technicians preferred the flat panel displays.

Christian: To my knowledge the Bell Canada technicians were offered both options – HMD and flat panel displays. In a public presentation, Brad Chitty of Bell Canada said that they had problems with irritated customers, whenever they appeared with HMDs at their door steps. So less obtrusive displays (HMDs) would be better even for interacting with peers such as customers.

Hannes: A 1999 International Data Corporation study estimated a US \$600 million market for a "fully functional PC that a person could wear as a peripheral to their clothing" by 2003. Before in 2005 Xybernaut filed for bankruptcy reorganization, it was a leading provider of wearable/mobile computing hardware and they sold more than 200 million shares, less than 10000 computers and never made profit. What do you think have been the reasons?

Christian: I don't want and cannot comment on Xybernaut's problems. In general: still in 2012, wearable computing (besides pick-by-voice) is a very small niche market, so maybe Data Corporation was wrong.

Hannes: TeXXmo was founded in Böblingen in 2005, as a sort of management buy-out of Xybernaut GmbH. How has your business developed since then?

Christian: Our daily business is distribution of industrial-grade Tablet PCs. We built up a brand and do quite well. Wearable computing is an R&D topic, which we follow in various research projects, and we introduced a mini-series of a commercially wearable computer system, which mostly serves pilot and university projects.

Hannes: Why do you think HMDs have not been very successful in industrial scenarios yet?

Christian: Price and weight are still too high! And none of the HMDs have been really ruggedized and durable.

Hannes: In the military sector HMDs seem to have a bigger success, what is different here?

Christian: Money seems to be less of an issue and with all the equipment soldiers have to carry anyway, the weight of a HMD seems neglectable; besides that: the motivation to save lives might help to overcome usability issues.

Hannes: What can you tell about the current market: Wearable and Mobile solutions for industrial usage and especially wearable solutions including HMDs?

Christian: The only thing which is for sure is that it's hard to predict when time will come for industrial wearables with HMDs. Maybe current developments, such as Google's project Glass can help speeding up the market. Motorola is working on a kind of industrial-grade PDA-based "*head-worn computer*"

with display. But we do not know, when such systems are commercially available and if they will be as chic and usable as these first prototypes promise.

Appendix C

FOUR CONDITION QUESTIONNAIRE

Definitionen der Beanspruchungsfaktoren

Geistige Anforderungen

Wie hoch waren die geistigen Anforderungen der Aufgabe?

Körperliche Anforderungen

Wie hoch waren die körperlichen Anforderungen der Aufgabe?

Zeitlicher Druck

Wie hoch war der zeitliche Druck bei der Aufgabe?

Leistung

Wie erfolgreich haben Sie die geforderte Aufgabe – Ihrer Ansicht nach – erfüllen können?

Anstrengung

Wie sehr mussten Sie sich anstrengen, um Ihre Leistung zu erreichen?

Frustration

Wie verunsichert, entmutigt, gereizt und verärgert waren Sie?

ID _____

Modalität: Papier (Text)

Die Aufgabe war leicht zu erlernen

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Die Aufgabe war unangenehm auszuüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich konnte die Aufgabe schnell ausüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich machte Fehler beim ausüben der Aufgabe

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Hast du spezielle Strategien angewendet um die Aufgabe auszuführen?

ID _____

Modalität: Papier (Text)

NASA-TLX

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

ID _____

Modalität: Papier (Text)

NASA-TLX

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

ID _____

Modalität: Papier (graphisch)

Die Aufgabe war leicht zu erlernen

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Die Aufgabe war unangenehm auszuüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich konnte die Aufgabe schnell ausüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich machte Fehler beim ausüben der Aufgabe

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Hast du spezielle Strategien angewendet um die Aufgabe auszuführen?

ID _____

Modalität: Papier (graphisch)

NASA-TLX

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

ID _____

Modalität: Papier (graphisch)

NASA-TLX

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

ID _____

Modalität: Audio

Die Aufgabe war leicht zu erlernen

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Die Aufgabe war unangenehm auszuüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich konnte die Aufgabe schnell ausüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich machte Fehler beim ausüben der Aufgabe

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Hast du spezielle Strategien angewendet um die Aufgabe auszuführen?

ID _____

Modalität: Audio

NASA-TLX

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

ID _____

Modalität: Audio

NASA-TLX

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

ID _____

Modalität: HMD

Die Aufgabe war leicht zu erlernen

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Die Aufgabe war unangenehm auszuüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich konnte die Aufgabe schnell ausüben

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Ich machte Fehler beim ausüben der Aufgabe

1	2	3	4	5	6	7
Trifft keineswegs zu	Trifft nicht zu	Trifft nicht wirklich zu	Weiß nicht	Trifft teilweise zu	Trifft zu	Trifft voll zu

Erklärung (optional):

Hast du spezielle Strategien angewendet um die Aufgabe auszuführen?

ID _____

Modalität: HMD

NASA-TLX

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

ID _____

Modalität: Papier HMD

NASA-TLX

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

ID _____

Platziere die verschiedenen Methoden (1. bis 4. Platz):

Insgesamt

__ Papier (Text) __ Papier (graphisch) __ Audio __ HMD

Leicht zu lernen

__ Papier (Text) __ Papier (graphisch) __ Audio __ HMD

Komfort

__ Papier (Text) __ Papier (graphisch) __ Audio __ HMD

Geschwindigkeit

__ Papier (Text) __ Papier (graphisch) __ Audio __ HMD

Korrektheit

__ Papier (Text) __ Papier (graphisch) __ Audio __ HMD

Andere Anmerkungen zu den Methoden (optional)?

Bitte mache folgende Angaben zu dir:

Geschlecht: __ männlich __ weiblich

Dominantes Auge: __ rechts __ links

Rechts-/links-Händer: __ rechts __ links

Alter: _____

Appendix D

OPTIMIZATIONS QUESTIONNAIRE

ID: _____

LRF: Ja Nein

PDA: Ja Nein

0. Allgemeines

Frage 0.1

Wie alt sind Sie?

Geschlecht

M W

Frage 0.2 (nur LRF)

Finden Sie das Prinzip der Grifferkennung gut?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 0.3

Tragen Sie eine Brille – Sehhilfe?

Ja, meistens <input type="checkbox"/>	Ja, nur zum Lesen <input type="checkbox"/>	Nein, gar nicht <input type="checkbox"/>
------------------------------------------	-----------------------------------------------	---------------------------------------------

Frage 0.4

Tragen Sie Kontaktlinsen? [contact lenses, kontaktlens, lente a contatto]

Ja, meistens <input type="checkbox"/>	Ja, manchmal <input type="checkbox"/>	Nein, gar nicht <input type="checkbox"/>
------------------------------------------	------------------------------------------	---------------------------------------------

Dominates Auge

Rechtes Linkes

Rechts- / Linkshänder

Rechtshänder Linkshänder

Frage 0.5

Haben bzw. wie lange haben Sie Kommissioniererfahrung?

1. Fragen zur Anzeige: einfarbig/ ohne Markierungen

Frage 1.1

Wie sind Sie mit der Anzeige der Kommissionieraufträge zu Recht gekommen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 1.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 1.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 1.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 1.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 1.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 1.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 1.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

1.9 NASA-TLX

ID _____

Modalität: Einfarbig und ohne Markierung

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

2. Fragen zur Anzeige: einfarbig/ mit Zahlen

Frage 2.1

Wie empfanden Sie die Verwendung von Zahlen an den Fächern?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 2.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 2.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 2.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 2.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 2.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 2.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 2.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

2.9 NASA-TLX

ID _____

Modalität: Einfarbig und mit Zahlen

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

3. Fragen zur Anzeige: farbig/ ohne Markierungen

Frage 3.1

Wie empfanden Sie die Verwendung von farblichen Markierungen an den Regalen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 3.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 3.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 3.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 3.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 3.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 3.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 3.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

3.9 NASA-TLX

ID _____

Modalität: Farbig und ohne Markierung

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

4. Fragen zur Anzeige: farbig/ mit Symbolen

Frage 4.1

Wie empfanden Sie die Verwendung von den Symbolen an den Regalen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 4.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 4.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 4.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 4.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 4.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 4.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 4.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

4.9 NASA-TLX

ID _____

Modalität: Farbig und mit Symbolen

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

5. Fragen zur Anzeige: farbig/ mit Symbolen/ mit Bezeichnungen

Frage 5.1

Wie empfanden Sie die Verwendung von Bauteilbezeichnungen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 5.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 5.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 5.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 5.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 5.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 5.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 5.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

5.9 NASA-TLX

ID _____

Modalität: Farblich und mit Symbolen und Bauteilbezeichnung

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

6. Fragen zur Anzeige: farbig/ mit Symbolen/ mit Bildern

Frage 6.1

Wie empfanden Sie die Verwendung von Bildern der Bauteile?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 6.2

Wie gut haben Sie erkennen können aus welchem Regal Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 6.3

Wie gut haben Sie erkennen können für welchen Montageumfang Sie kommissionieren müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 6.4

Wie gut haben Sie erkennen können welche Bauteile Sie greifen müssen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Frage 6.5

Haben Sie erkennen können wenn Sie ein Teil erfolgreich kommissioniert haben?

Ja <input type="checkbox"/>	Nein <input type="checkbox"/>
--------------------------------	----------------------------------

Frage 6.6

Haben Sie nach dem Beenden des Kommissionierauftrags das Gefühl, dass Bauteile fehlen?

Ja, meistens <input type="checkbox"/>	Manchmal <input type="checkbox"/>	Nein, selten <input type="checkbox"/>
------------------------------------------	--------------------------------------	------------------------------------------

Frage 6.7

Gab es Dinge, die Sie gestört haben? Wenn ja, was?

Frage 6.8

Gibt es Dinge, die Ihnen besonders gefallen haben?

6.9 NASA-TLX

ID _____

Modalität: Farblich und mit Symbolen und Abbildungen der Bauteile

Ranking verschiedener Arbeitsbelastungs-Faktoren

Kreise bei allen angegebenen Paaren den jeweils bedeutenderen Faktor für die Arbeitsbelastung an

Geistige Anforderung	oder	Körperliche Anforderung
Geistige Anforderung	oder	Zeitlicher Druck
Geistige Anforderung	oder	Leistung(sdruck)
Geistige Anforderung	oder	Anstrengung
Geistige Anforderung	oder	Frustration
Körperliche Anforderung	oder	Zeitlicher Druck
Körperliche Anforderung	oder	Leistung(sdruck)
Körperliche Anforderung	oder	Anstrengung
Körperliche Anforderung	oder	Frustration
Zeitlicher Druck	oder	Leistung(sdruck)
Zeitlicher Druck	oder	Frustration
Zeitlicher Druck	oder	Anstrengung
Leistung(sdruck)	oder	Frustration
Leistung(sdruck)	oder	Anstrengung
Frustration	oder	Anstrengung

Bewertung der Arbeitsbelastungs-Faktoren

Kreuze entsprechend deines Empfindens jeweils eins der Kreise in den Skalen an

Geistige Anforderungen

Gering Hoch

Körperliche Anforderungen

Gering Hoch

Zeitlicher Druck

Gering Hoch

Leistung

Gering Hoch

Anstrengung

Gering Hoch

Frustration

Gering Hoch

7. Navigation

Wie sind sie mit der Navigation zu Recht gekommen?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

8. Griffenerkennung

Wie finden Sie die Griffenerkennung?

sehr gut <input type="checkbox"/>	gut <input type="checkbox"/>	neutral <input type="checkbox"/>	schlecht <input type="checkbox"/>	sehr schlecht <input type="checkbox"/>
--------------------------------------	---------------------------------	-------------------------------------	--------------------------------------	-------------------------------------------

Gab es konkrete Probleme bei der Griffenerkennung?

Das System ist zu fehleranfällig <input type="checkbox"/>	Das System ist zu träge <input type="checkbox"/>	Keine Probleme <input type="checkbox"/>
--------------------------------------------------------------	-----------------------------------------------------	--------------------------------------------

9. Ranking

Platziere die verschiedenen Methoden (1. bis 6. Platz):

9.1 Insgesamt

- einfarbig/ ohne Markierungen
- einfarbig/ mit Zahlen
- farbig/ ohne Markierungen
- farbig/ mit Symbolen
- farbig/ mit Symbolen/ mit Bezeichnungen
- farbig/ mit Symbolen/ mit Bildern

9.2 Leicht zu lernen

- einfarbig/ ohne Markierungen
- einfarbig/ mit Zahlen
- farbig/ ohne Markierungen
- farbig/ mit Symbolen
- farbig/ mit Symbolen/ mit Bezeichnungen
- farbig/ mit Symbolen/ mit Bildern

9.3 Komfort

- einfarbig/ ohne Markierungen
- einfarbig/ mit Zahlen
- farbig/ ohne Markierungen
- farbig/ mit Symbolen
- farbig/ mit Symbolen/ mit Bezeichnungen
- farbig/ mit Symbolen/ mit Bildern

9.4 Geschwindigkeit

- einfarbig/ ohne Markierungen
- einfarbig/ mit Zahlen
- farbig/ ohne Markierungen
- farbig/ mit Symbolen
- farbig/ mit Symbolen/ mit Bezeichnungen
- farbig/ mit Symbolen/ mit Bildern

9.5 Korrektheit

- einfarbig/ ohne Markierungen
- einfarbig/ mit Zahlen
- farbig/ ohne Markierungen
- farbig/ mit Symbolen
- farbig/ mit Symbolen/ mit Bezeichnungen
- farbig/ mit Symbolen/ mit Bildern

9.6 Andere Anmerkungen zu den Methoden (optional)?

10. Bewertung

Bewerten Sie das System auf einer Skala von 1 bis 6, wobei 1 sehr gut bedeutet und 6 schlecht (Schulnotensystem).

Tragekomfort beim Wearable

1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	4 <input type="checkbox"/>	5 <input type="checkbox"/>	6 <input type="checkbox"/>
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Tragekomfort beim PDA

1 <input type="checkbox"/>	2 <input type="checkbox"/>	3 <input type="checkbox"/>	4 <input type="checkbox"/>	5 <input type="checkbox"/>	6 <input type="checkbox"/>
-------------------------------	-------------------------------	-------------------------------	-------------------------------	-------------------------------	-------------------------------

11. Fehler, Probleme, Informationen beim Kommissionieren

Gibt es von Ihrer Seite aus Verbesserungsvorschläge zu dem von Ihnen getesteten tragbaren Computer?

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Glossary

AR augmented reality.

batch picking Multiple orders are picked in parallel by just one order picker.
See also page 7.

binocular rivalry see page 117.

eye dominance see page 118.

graphical pick chart A graphical representation of what to pick within a shelf (and where to put the items).

head-mounted display A head-mounted display is a heads-up display that is worn on the head.

heads-up display A heads-up display shows information in the field of vision of a user while performing a task.

high density picking environment A picking environment where the workers have to pick many items related to the traveled distance.

HMD head-mounted display.

HUD heads-up display.

look-around HMD A HMD that blocks the light of the environment within the field of view of the virtual screen. See also page 110.

LRF laser rangefinder.

mobile scanning device A mobile computer with RF or bar code scanner. See also page 10.

pick chart graphical pick chart.

pick-by-HMD see page 77.

pick-by-light see page 11.

pick-by-paper see page 78.

pick-by-Tablet see page 78.

pick-by-voice see page 11.

ring bar code scanner A bar code scanner worn on a finger. See also page 26.

see-through HMD A HMD where it is possible to see the environment behind the virtual screen. See also page 110.

shelf shelving unit.

sort-while-picking Multiple orders are picked and sorted in parallel by just one order picker. See also page 7.

wrist-worn device A wrist-worn wearable computer. See also page 26.