RF-Pick: Comparing Order Picking Using a HUD with Wearable RFID Verification to Traditional Pick Methods

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ABSTRACT

Order picking accounts for 55% of the annual $60 billion spent on warehouse operations in the United States. Reducing human-induced errors in the order fulfillment process can save warehouses and distributors significant costs. We investigate a radio-frequency identification (RFID)-based verification method wherein wearable RFID scanners, worn on the wrists, scan passive RFID tags mounted on an item's bin as the item is picked; this method is used in conjunction with a head-up display (HUD) to guide the user to the correct item. We compare this RFID verification method to pick-to-light with button verification, pick-to-paper with barcode verification, and pick-to-paper with no verification. We find that pick-to-HUD with RFID verification enables significantly faster picking, provides the lowest error rate, and provides the lowest task workload.

ACM Classification Keywords

H.5.2. Information interfaces and presentation (e.g., HCI): Miscellaneous; User Interfaces-Evaluation/methodology

Author Keywords

Order Picking; Wearable Computers; Head-Up Display; RFID; Augmented Reality

INTRODUCTION AND RELATED WORK

Order picking, the process of collecting items in a specified quantity to fulfill a customer's order, accounts for over $30 billion in annual warehousing expenditures in the United States alone [2, 3]. Currently, 80% of order picking is performed by humans using paper-based pick lists [8]. Previous research has studied the impact of various technologies in order picking. Weaver et al. compared pick-to- head-up display (pick-to-HUD) to pick-to-voice and found HUDs to be significantly faster [11]. Guo et al. compared pick-to-paper, pick-to-light, and pick-to-HUD [5]. Pick-to-HUD was faster than the other methods. Other studies have reached similar conclusions [1, 13].

While HUD has already been shown to have major improvements over other methods in terms of efficiency, accuracy, and comfort, previous studies found that HUD systems trended toward more errors than pick-to-light systems [13]; however, the results were not statistically significant. Wu et al. managed to reduce errors in pick-to-HUD by using a weight-based verification system [12]. Industrial weight systems, however, typically require the picker to place one item on the scale at a time, which impacts the HUD's speed advantage. Iben et al. implemented pick verification by coupling laser rangefinders with a HUD [6]. The combined system, however, was not an improvement over pick-to-light with button verification as the picker tended to brush through the rangefinder's region creating false triggers.

We improve upon pick-to-HUD order picking by using two wearable RFID readers, attached to the picker's wrists, which detect passive tags placed in individual bins. These wearable bands allow real-time pick verification while keeping both hands free for the task.

Radio Frequency Identification (RFID) technology

Although RFID technology has been mature for over a decade, the largest barrier to adoption has been the unit cost of passive

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RFID tags which can be up to $0.10 [10]. For an RFID-based verification method to be useful, warehouses must install passive RFID tags on every item or every pick bin. Printed barcode labels, in contrast, cost less but require large enough surface area so that the barcodes can be read at a distance. For an automobile pick line with 1000 bins of items, instrumenting every bin with a passive RFID tag would cost about $700 more than the cost of the equivalent barcodes, suggesting that the functional cost savings may well be worth this initial overhead.

Pick and Verification Methods

We test four order picking methods: pick-to-paper with no verification (the industry default of using printed sheets specifying item numbers and quantities), pick-to-paper where the picker verifies a pick by scanning a barcode on the item's bin, pick-to-light where the picker confirms a pick by pressing a button mounted in front of the item's bin, and pick-to-HUD where verification occurs when the picker's wrist passes a passive RFID tag mounted on the item's bin. We have chosen to use a shorthand notation to reference these pick methods: <guidance mechanism>-<error verification mechanism>; therefore, we refer to the aforementioned methods respectively as Paper-None, Paper-Barcode, Light-Button, and HUD-RFID.

Pick-to-Paper with No Verification (Paper-None)

Pick-to-paper with no verification is the most rudimentary approach to order picking and serves as the baseline for comparison against other order picking methods. The approach is very popular [9] as it is intuitive to most pickers and requires very little training or upfront monetary investment other than the cost of the paper itself. The lack of a verification method, however, introduces significant concerns. Picking accuracy is solely based on the picker's attentiveness, which is burdened by the constant need to shift the attentional and physical focus of the eyes from paper to the environment.

Pick-to-Paper with Barcode Verification (Paper-Barcode)

Adding a simple barcode scanner to pick-to-paper has become an industry staple for verifying picks. There are many forms of barcodes used in warehouses today including 1D (e.g. UPC, EAN, GS1, etc.), 2D (e.g. QR Code, Datamatrix, etc.), and more recently 3D barcodes. Barcode scanners incur a cost to the speed of order picking, but they also provide potential advantages to the warehouse. First, they reduce the number of incorrect picks, as the picker is required to verify each item with a scan. Second, they allow the warehouse management system (WMS) to be aware of the last-scanned location of the picker, which enables the implementation of more advanced optimization methods, like task interleaving, path finding, etc.

Pick-to-Light with Button Verification (Light-Button)

In pick-to-light, pickers receive the picking information via small LED displays attached to each bin. Pick-to-light without verification has been shown to be significantly faster than pick-to-paper [5]. The addition of button verification may have a negative effect on speed, but it greatly reduces the number of errors [13], making it one of least error-prone methods available [12].

Pick-to-light is commonly implemented in dense picking environments, where the high installation cost ($100-130 per pick location) is counterbalanced by the large number of picks per unit of distance. Because of the hardware and the wiring, pick-to-light is not ideal for warehouses that require frequent layout rearrangements, and it can be difficult to support simultaneous picking by several pickers.

Figure 1. Android phone, Google Glass, and wearable RFID readers

Pick-to-HUD with RFID Verification (HUD-RFID)

Pick-to-HUD has been repeatedly [5, 11, 12, 13] shown to be the fastest method in order picking. Previous authors [5, 12, 13], have attempted to measure HUD's accuracy compared to pick-to-light, and while they have found HUDs to trend higher in errors, the results are not statistically significant due to the small number of overall errors. For this experiment, we designed our pick tasks to elicit as many errors as possible; our primary goal is to study errors while maintaining speed. While this setup is different than previous studies, we can still compare HUD and RFID independently by comparing to the Paper-None baseline. In this work, we propose a solution which combines the speed of pick-to-HUD with the verification ability of wearable RFID readers.

IMPLEMENTATION

We used Google Glass for our Heads-Up Display and Ubimax xBands for our wearable RFID readers. We also used a mobile device, the Samsung Galaxy A3 (2016), to manage and oversee the experiment. (Figure 1)

The two wearable RFID readers were connected via a Bluetooth Low Energy (BLE) session to the mobile device which was in turn connected to the HUD. When a user reached into a bin, the band would read the passive RFID tag located on the lip of the bin and would send the encoded bin tag string to the mobile device. Adjusting the reader's power was a crucial factor for the effectiveness of our method. Too high a power, and the readers would pick up the nearby tags as well. Too low, and the subjects would struggle to get a valid scan, making the whole experience much less smooth.

The mobile device would receive the scan, decide whether it was correct, and would update the HUD user interface appropriately. The user would also hear either a confirmation or error tone after each pick.

User Interface

In order for HUD applications to be successful, special care has to be given to the way the information is displayed. We used a rapid iteration approach, designing our UI based on user feedback. Are users getting the messages we want them to? To achieve that, we attempted to create a UI that closely resembled the physical world (Figure 2).

We color-coded our UI elements with the same color-pattern we use on our racks. We used a white tag on the top of the screen to identify the active rack and added faded-out gray cells on the side to help the user intuitively find the active rack.

Error Recovery with HUD

Whenever the wrong pick was detected, the user was sent an alert. There were three types of error alerts: incorrect item picked, incorrect rack, and incorrect receive bin. All error alerts where accompanied by a negative sound stimulus.

Incorrect Item Picked

In this case, the UI draws a small red X on the incorrect bin scanned. If the user scans the incorrect bin again, the small red X is removed.

Incorrect Rack

If the user scans an incorrect rack (e.g. B instead of A), the UI flashes a red X briefly as displayed in Figure 3.

Incorrect Receive Bin

This error occurs when the picker places the items in the wrong receive bin. Here, the UI would show the items that were incorrectly placed and their respective quantities. It would also indicate the correct receive bin as shown in Figure 4. The user would tap the Glass to dismiss.

ENVIRONMENT

We utilize a similar environment to Wu et al. [12] featuring a dense picking environment with two 4 x 3 matrices ("racks") of source bins (each containing about 50 instances of household items like batteries or paperclips). These two racks were positioned to the left and in front of a cart containing three receive bins. Each source bin is outfitted with a label indicating its position in the rack matrix, a printed barcode encoding this unique position, a seven-segment LED and button confirmation device (both used solely in pick-to-light - see Figure 5), and a passive RFID tag encoding the position information. See Figures 6 and 7.

In the pick-to-light trials, these two racks are connected through Ethernet interfaces to a laptop controlling the display of the LEDs and responding to the push of the confirmation buttons. Figure 8 illustrates how the different physical, hardware, and software components of our setup interact.

In the pick-to-barcode trials where barcode verification is used, the wireless barcode scanner is connected directly to a computer handling scans of the source and receive bins. Upon scan of the wrong source or receive bin, the computer plays an error tone through an external stereo speaker clearly audible to the user, informing them of their error.

In the pick-to-HUD trials where RFID verification is used, the LED light array and barcode error tone systems are not utilized.

We define the following terms to describe our setup:

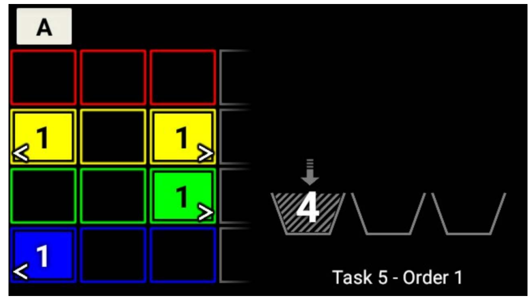

Figure 2. The left hand side of the screen corresponds to the active rack, while the right hand side of the screen corresponds to the cart.

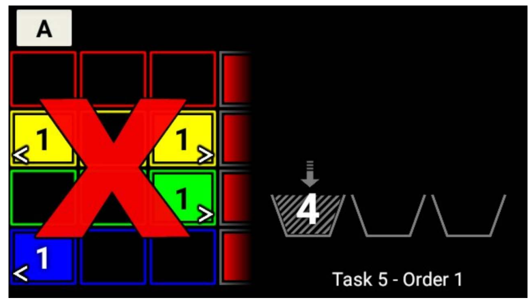

Figure 3. A screenshot of the UI, showcasing an incorrect rack error.

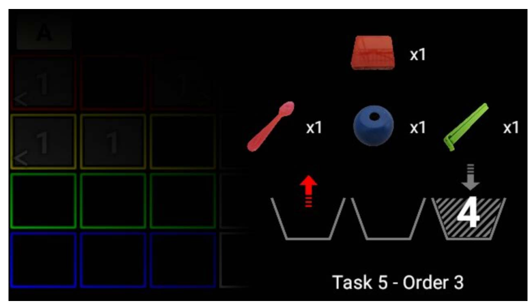

Figure 4. When the user places the picked items in the wrong receive bin, the heads up display will inform the user how to correct their mistake.

Figure 5. A source bin with identification methods. From top to bottom: a passive RFID, a two-digit seven-segment LED, a visual " 32" and a printed barcode.

- Item - A single item.
- Source Bin - The bin from which the picker picks a number of items.
- Receive Bin - The bin where the picker puts the items.
- Rack - A group of source bins. (A or B - 4 x 3).
- Cart - A group of receive bins (1 x 3) mounted on a wheeled cart.

We also define the following subdivisions for a task:

- Pick - An acquisition of items from a source bin.
- Place - An unloading of items into a receive bin.
- Suborder - Picking all the items from a single rack, and placing them in a single receive bin.
- Order - An order is housed in a single receive bin and is what will go to the end customer. Each order is a set of two suborders.
- Task - A task is a set of three orders; one for each receive bin.

A single task was conducted as follows:

1. Pick items from rack A and place them in the first receive bin, to complete the first suborder.
2. Proceed to fulfill the next two suborders and then move on to the other rack and repeat the process.
3. Once all 6 suborders have been conducted, A1-3 and B1-3, the task is completed.

STUDY METHODOLOGY

Based on previous research, we held the following *a priori* hypotheses:

- H1: Average task time of HUD-RFID is less than average task time of all other methods
- H2: Average item error of HUD-RFID is less than average item error of all other methods
- H3: HUD-RFID has lower subjective workload than all other methods
- H4: HUD-RFID is overall preferred over all other methods

We conducted a within-subjects user study to evaluate the pick methods. Our study consisted of 12 participants (eight male, four female). All participants were right-hand dominant. Nine participants were right-eye dominant and three were left-eye dominant. All participants were first-time order pickers. We counterbalanced our conditions using a 4-by-4 balanced Latin square to help avoid ordering effects. Participants were compensated $30 for their participation in the two hour study and were instructed to perform the picks as quickly and as accurately as possible.

Each subject would first go through a training session of five tasks per method in order to help extinguish learning effects (Figure 9). During training, researchers would actively assist participants in answering any questions they had about the method they were running.

Ten tasks per method were utilized in the testing phase. In order to induce more errors than prior work [12], the number of picks in each suborder was selected in a two phase mechanism. First the number of source bins per order was selected from a non-uniform distribution where the probability selecting four bins was 90%, five bins was 5%, and six bins was 5%. Second, the number of items per each selected source bin was selected from a second non-uniform distribution where the probability of selecting one item from the bin was 87%, two items was 8%, and three items was 5%.

The human mind typically stores 3-5 items in its short-term memory. We employed this method of generating pick lists to push the limits of our participants' short-term memory [4, 7]. We posited that the large number of items (4-18 per suborder) would make the participants more likely to make a mistake than previous experiments.

Test sessions were video-recorded and timed. Three of the methods were timed using an automatic logging system and one (Paper-None) was timed with a stopwatch and recorded by hand by an attending researcher. After the experiment, participants completed a NASA-TLX survey for each pick method and an overall ranked-preference survey at the conclusion of their participation in the study.

Labeling and Categorizing Incorrect Orders

Error checking was performed by taking pictures of the receive bins after each task and comparing the receive bins with the expected items, as shown in Figure 10.

We first labelled all the images as correct or incorrect. After that, we revisited the incorrect ones and further separated them into different categories which are consistent with previous literature [13].

We define the following categories of errors:

- Missing Item - An item ordered is not received.
- Insertion - An extra item is added to an order.
- Substitution - Equivalent to a combination of insertion and missing item; it is when the wrong item is received in place of another item
- Pick too few - The correct source bin is chosen but there are not enough items picked. Equal to the number of items missing.
- Pick too many - The correct source bin is chosen but there are too many items picked.

ANALYSIS AND RESULTS

We report average task time, average item error, subjective task load, and user preferences for all four pick and verification methods.

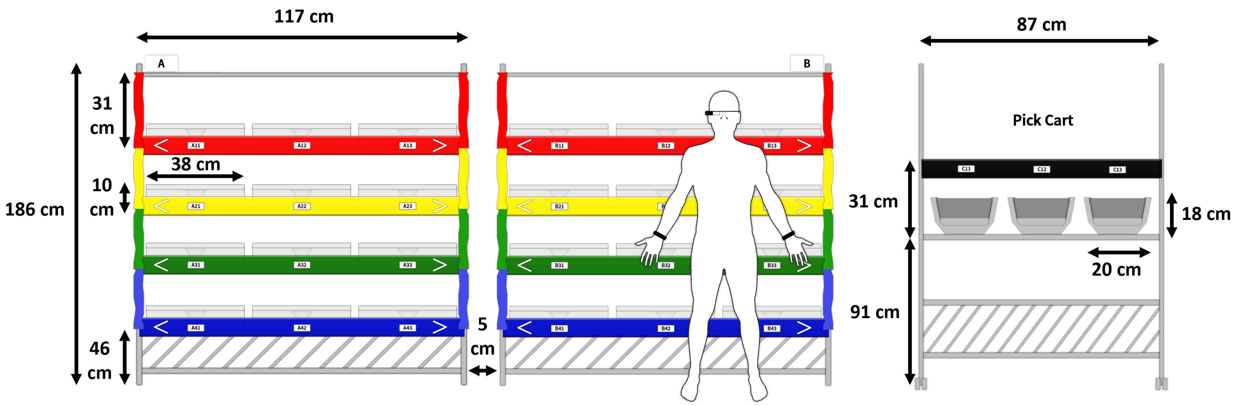

Figure 6. Our experimental environment consists of two racks (named A and B) and a cart. Each rack has 12 source bins, and the cart has three receive bins (bottom row not used).

Figure 7. Image of experimental environment.

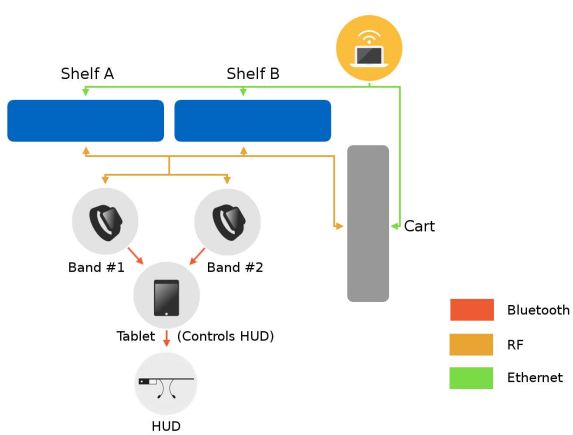

Figure 8. System architecture.

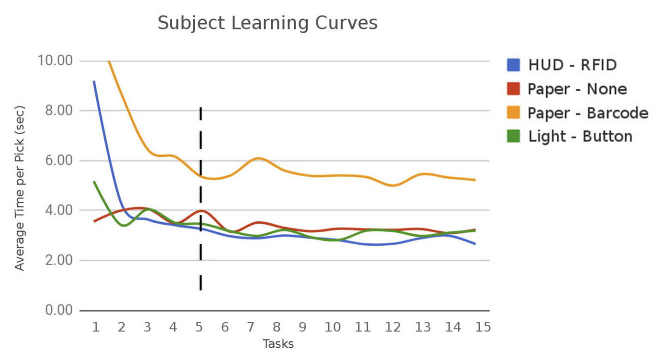

Figure 9. The time per pick for every task in order. The dashed line separates the training from the testing phase.

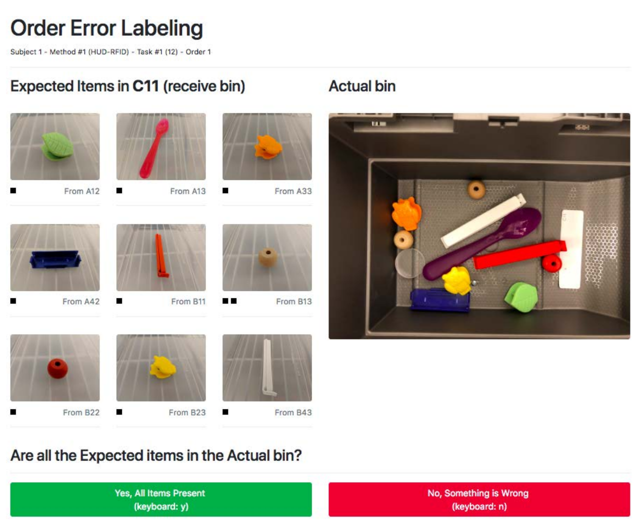

Figure 10. Our post-study error labeling interface.

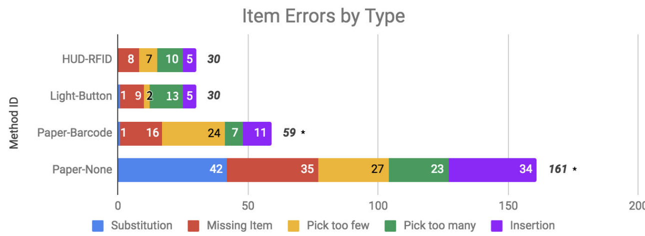

Figure 12. Breakdown of order errors by type.
*** indicates a statistically significant difference between means.**

Average Task Time

We used pairwise one-tailed t-tests with Benjamini-Hochberg correction for multiple hypothesis testing to test the null hypotheses that the average task time of the HUD-RFID tasks was greater than or equal to all other methods. The null hypothesis was rejected in all cases. In other words, HUD-RFID was faster than every other method we tested. Figure 11 compares the average task time for each method evaluated.

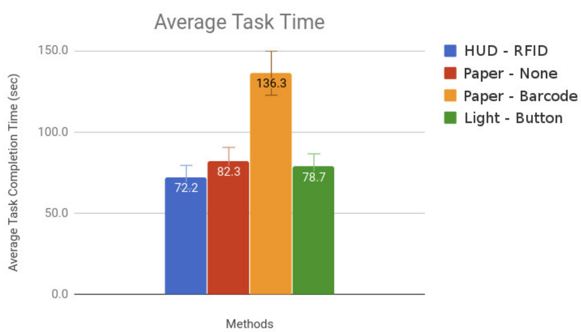

Figure 11. Average task time for each method.

Errors

In Figure 12, we display the total number of errors for each method with a breakdown by error type.

To test the significance of the error rate between different picking methods, we use pairwise one-tailed t-tests with Benjamini-Hochberg correction for multiple hypothesis testing to test the null hypothesis that the average item error of HUD-RFID is greater than the average item error of all other methods. We can reject the null hypothesis and conclude that average item error of pick-to-HUD with RFID is less than the average item error of pick-to-paper with no verification and pick-to-paper with barcode verification.

When comparing HUD-RFID with Light-Button, the difference in mean errors is not statistically significant, and the error distributions are similar.

User Preferences

In the same vein, we made interesting observations on the user preferences. We used the one-tailed Wilcoxon Signed-Rank test to test the null hypothesis that overall preference for HUD-RFID was less than the overall preference for all other methods. When comparing HUD and Barcode, ($W = 0$) the result was statistically significant. When comparing HUD and Paper, ($W = 13$) the result was statistically significant. However, when comparing HUD and Light, ($W = 22.5$) the result was not statistically significant.

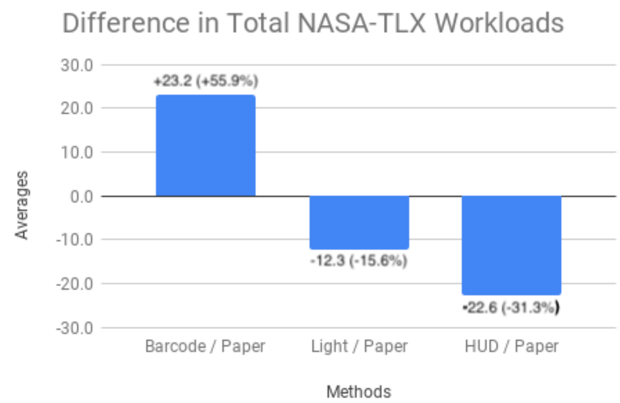

Figure 13. The absolute differences between our comparison three methods and our reference method: Paper-None (average workload = 58).

Table 1 outlines average user ratings of our four methods through a ranked preference survey.

	HUD-RFID	Light-Button	Paper-Barcode	Paper-None
Overall	1.50	2.00	3.92	2.58
Learnability	1.92	2.00	3.83	2.17
Comfort	2.42	1.33	3.92	2.33
Speed	1.33	2.17	3.92	2.50
Accuracy	1.08	2.17	3.25	3.42

Table 1. User Preferences

Overall Task Load

We employed the NASA Task Load Index to measure the workload of each method. The survey quantifies the subjects perception of the mental demand, physical demand, temporal demand, performance, effort, and frustration with a task. The measure ranges from 0 to 100 with larger values indicating higher load. Figure 13 details our results.

We used the one-tailed t-tests with Benjamini-Hochberg correction for multiple hypothesis testing to test the null hypothesis that overall workload for HUD-RFID was higher than that for all other methods. All differences in means versus HUD-RFID reached statistical significance.

DISCUSSION AND FUTURE WORK

In terms of task times, our results are largely consistent with the results from previous work. The observed percentage improvement in errors compared to Pick-to-Paper was 75% for HUD-RFID, 82% for Light-Button, and 64% for Paper-Barcode. However, the number of order errors is significantly higher than in previous studies as we sought to purposefully increase the number of errors in our study to better understand what types of errors RFID-based verification can prevent.

Error Types across Pick Methods

We proceeded to analyze the individual item errors in terms of their type. By breaking down the errors into type, we can separate errors into different classes based on severity. For example, less severe errors are insertion and pick too many because they increase the company cost but do not generate customer dissatisfaction. More severe errors include missing item, substitution, and pick too few.

Causes of Errors

At this point, we wanted to investigate the cause of errors for each method. Did the errors result from a lapse of attention, an unclear rule, or a systemic issue? How could a subject not pick an item in the Light-Button method, for example, when clicking the bin button is the only way to proceed to the next task? We believed that such an insight would help us find faults in our existing solutions.

None of the methods we used were able detect pick-too-many and pick-too-few errors, so we excluded these error types from the analysis.

HUD-RFID

Most errors recorded for this method were preventable.

A number of errors were either directly or indirectly linked to a faulty RFID band (xBand) which often prevented subjects from scanning a certain tag. This problem led subjects to favor one hand over the other and had a significant impact on their flow and immersion in the process. In one such example, a subject reached into a bin and picked a single item. He then reached with his other hand into a different bin and scanned the tag but stopped before completing the pick as he realized that the previous pick was not registered by the faulty RFID band. He went back and re-scanned the first bin, but forgot to complete the second pick, thus causing a missing item error.

Another important cause of errors involved subjects placing items in the wrong receive bin. In Figure 4 we presented our attempt to aid the subjects for correcting such errors on the spot, before they impact the end customer. Our method helped prevent a number of such errors, but was not optimal. The process required subjects to remove all misplaced items from the wrong receive bin before placing them in the correct one. There were issues, however, when subjects attempted to correct such errors in batches which would cause our system to proceed after the first place and would not allow them to correct the rest.

Finally, a small number of errors were caused when the RFID bands incorrectly scanned a tag under the desired bin. This problem was caused by the variable scan distance of the bands, possibly influenced by metal objects in their environment. In one such example, a subject had to pick items from bin B43, but incorrectly reached into bin B33 which is directly on top. The RFID band registered and scanned both tags which led the subject to believe he made the correct pick.

Light-Button

In Light-Button, errors were more straightforward.

Many errors were caused by lapses in attention. Subjects would click one button and pick from a different bin. This type of error was surprisingly common because the vast majority of subjects pushed buttons with one hand and picked items with the other, which increased the probability of a human error. Such errors would not affect HUD-RFID due to the fact that the hand that scans is also the hand that picks.

The rest of the errors were wrong receive bin errors. Light-Button has no way of correcting these errors, so they took a toll even if the subject recognized the mistake immediately.

Paper-Barcode

In Paper-Barcode, many errors were caused by the cognitive distance between verification and pick. Subjects would scan a tag and not complete a pick, or would scan a number of tags in a batch and would only pick a portion of them.

A number of errors were also caused by an inherent problem of our implementation. Our barcode scanner did not include a display and thus could not give subjects a clear status of their progress. Subjects would miss a pick, and the system would not allow them to proceed. When that happened, subjects could not easily find which items they were missing. Some proceeded to scan every tag in sequence, which generated a number of missing item errors. In future study design, we could improve the barcode system by adding a display to the scanner device.

Paper-None

Because pick-to-paper offers no verification, most errors were straightforward. Subjects would skip some picks, perform others incorrectly and some would even pick from the wrong racks all together.

Substitution errors are understandably higher than in the other three methods that offer some form of confirmation for users. Any form of verification adds a second, system-enforced check on the user's behavior and will reduce substitution errors.

One of our main takeaways is that the further one distances the verification from the pick, either in time or space, the more human errors will be induced. This result is promising for the HUD-RFID method which has the verification embedded in the pick.

Subject Tactics to Overcome Technological Limitations

HUD-RFID

We observed users taking time to find the optimal way to move their hands in order to find the tags. After training, users would be able to scan the correct bins and would have less unintended scans with other bins near the vicinity.

Light-Button

We also observed that pickers typically step back to view the entire shelving unit and then scan the entire rack from top to bottom to find bins with remaining items. This observation is consistent to behaviors observed in Guo, et al. [5].

Paper-Barcode

We observed that subjects struggled to hold both the paper-list and the scanner whilst picking items. Some subjects attempted to free one hand for picking by holding both the barcode scanner and paper in one hand. Others collected items on their clipboard and then deposited them into the receive bin by sliding them off. Finally, some would first scan several bins, memorize them and then pick all the items at once. The fastest subject decided to hang the clipboard from the rack and picked the items with the free hand.

Post-hoc Observations

A surprising post-hoc observation was the difference between Pick-to-Paper with Barcode and Pick-to-Paper with No verification. We anticipated that Pick-to-Paper with Barcode would be extremely similar to Pick-to-Paper in terms of time - barcode scan actions are generally thought of as quick. However, there is a statistically significant difference in the timings ($p < 0.001$).

It would be interesting to investigate further into wearable barcode scanners to see if it could minimize the time taken for Pick-to-Paper with Barcode.

CONCLUSION

We explored a novel wearable RFID-based verification method to understand the per task speed and accuracy improvements of HUD-RFID compared to standard methods. We found that HUD-RFID was faster than all other methods and that errors occurred significantly less when compared to pick-by-paper with no verification and pick-by-paper with barcode verification. In terms of overall preference and workload, HUD-RFID was the most preferred and offered clear usability and comfort benefits. Considering the high implementation costs of pick-to-light, the high error rate of pick-to-paper, and the discomfort of pick-to-paper with barcode verification, pick-to-HUD with RFID verification offers a strong and cost-effective solution to fast and accurate order picking.

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