Entrepreneurial Applications of Augmented Reality in Product Placement on Shelves

Nadhif Haikal Farhansyah[1*], Hadziq Fabroyir[2]
[1,2]Faculty of Intelligent Electrical and Informatics Technology, Sepuluh Nopember Institute of Technology, Indonesia
[1]neorocket64@gmail.com, [2]hadziq@its.ac.id
***Corresponding Author**

Article Info

Article history:

Submission December 11, 2024
Revised January 20, 2025
Accepted December 9, 2025
Published January 19, 2026

Keywords:

Augmented Reality
Product Placement
Guidance System
Handheld Devices
Wearable Devices

ABSTRACT

A Planogram automation system has been developed to maximize the effectiveness of product arrangements on store shelves. However, its design could not be used at its full potential because of human errors that frequently occur when employees attempt to place products according to a predetermined planogram. These errors reduce both accuracy and efficiency in the implementation process. Previous research addressed this challenge by proposing solutions in the form of automatic planogram compliance supervisors that utilize object detection technology to detect deviations. **In contrast**, this work proposed another approach to minimize human errors, namely by developing a real-time guidance system for product placement on the shelves using an Augmented Reality (AR) platform. **Two different** AR devices were implemented, consisting of a handheld Samsung Galaxy Tab S7 and a Video See Through (VST), Head Mounted Display (HMD) using Meta Quest 3, and their performance was compared to the conventional paper-based method. The system was evaluated through a user study involving 11 participants who had prior experience in product placement but no experience with HMD devices. **Results** showed that paper instruction achieved the best completion time in task performance, while no significant differences were found in error performance. HMD and paper instruction demonstrated similar outcomes on cognitive load, whereas handheld AR showed the worst performance and physical demand. **Based on** these results and post-task feedback, it can be concluded that although paper instruction remained the most favored method, the HMD demonstrated the greatest potential for future product placement guidance systems.

This is an open access article under the CC BY 4.0 license.

DOI: https://doi.org/10.34306/att.v8i1.572
This is an open-access article under the CC-BY license (https://creativecommons.org/licenses/by/4.0/)
©Authors retain all copyrights

1. INTRODUCTION

In the dynamic landscape of modern retail, technological advancement has become a driving force behind increased operational efficiency, customer engagement, and data driven decision making [1]. One crucial area that reflects this transformation is product merchandising, specifically the strategic arrangement of goods on store shelves. Traditionally, this process was performed manually based on general visual aesthetics or sales intuition. However, as competition has intensified and consumer behavior has become more complex, retailers are increasingly turning to systematized approaches like planogram design to optimize product placement [2]. Planogram systems offer a structured blueprint for product display that aims to enhance visibility, drive sales, and maximize the use of available shelf space. While these systems have introduced significant improvements in merchandising strategy, their effectiveness is frequently undermined by human error during execution on the store floor [3]. Issues such as incorrect product positioning, overlooking specific SKUs, or simple misinterpretation of printed instructions result in suboptimal outcomes that deviate from the original plan, thus impacting the intended marketing and operational goals. Moreover, correcting these errors post implementation often requires additional time and labor, reducing overall efficiency [4, 5].

Recognizing the limitations of manual and post corrective methods, this study introduces a novel approach that leverages the capabilities of Augmented Reality (AR), Technology to Provide real time visual guidance during the product placement process [6]. The concept is rooted in the idea of proactive intervention, where AR is used not merely as a monitoring tool but as an assistive medium that enhances human performance at the point of action. By overlaying virtual instructions directly onto the real world shelf environment, store staff can follow visual cues that guide them step by step in arranging products accurately and efficiently [7]. This solution was implemented using two types of AR platforms is a handheld device, which offers mobility and familiarity, and a Head Mounted Display (HMD), which allows for immersive, hands free interaction. The system was then evaluated through direct comparison with traditional paper based planogram methods to assess differences in task performance, user comfort, and cognitive load [8]. Through this comparative evaluation, the study not only seeks to determine which method offers the highest level of effectiveness but also explores the adaptability of AR technologies in real world retail settings, especially for personnel with varying levels of experience in using digital tools. The intention is to bridge the gap between complex system design and practical usability in store environments [9].

Beyond its technical and operational dimensions, this research also speaks directly to the broader narrative of sustainable development and responsible innovation [10]. It aligns with Sustainable Development Goal 8 by promoting decent work through the introduction of supportive digital infrastructure that enables workers to perform their tasks more accurately, with reduced mental and physical strain. Rather than replacing human roles, the proposed AR system empowers workers with tools that enhance their capabilities, fostering a work environment that is both productive and human centered [11]. At the same time, the project contributes to Sustainable Development Goal 9 by advocating for innovation within industry practices and encouraging the adoption of smart technologies that improve infrastructure without requiring excessive investment. The use of widely available, consumer grade devices ensures that the system can be scaled across various store formats without significant disruption or cost [12]. This democratization of technology allows even small and medium enterprises to benefit from innovation, supporting equitable economic growth. Furthermore, the shift from reactive correction to proactive guidance embodies a more sustainable operational philosophy, reducing waste in terms of time, effort, and potential lost sales. As the retail sector continues to evolve, embracing intelligent and accessible technologies like AR not only offers a competitive advantage but also plays a crucial role in building more resilient, inclusive, and future ready industries [13].

2. LITERATURE REVIEW

This section provides an overview of the technologies and methodologies related to Augmented Reality (AR), focusing on its use in guidance systems and how such systems are evaluated in user studies [14].

2.1. AR Systems

Augmented Reality is a technology that superimposes digital content into the real world through devices capable of perceiving physical surroundings [15]. This is achieved by combining visual data captured from the environment with virtual elements generated by the system. To accurately place virtual objects within real environments, AR systems rely on techniques that map and understand the spatial layout of rooms and objects, a process often referred to as Simultaneous Localization and Mapping (SLAM) [16]. SLAM helps create spatial maps based on device movement and environmental features. In addition to SLAM, a more accessible and widely used method is based on fiducial markers [17]. These markers are designed to be detected by a camera and provide spatial orientation by encoding position and rotation data. Marker based systems, such as those using square coded patterns, allow for precise overlay of 3D objects in relation to the real world view captured by the device camera [18]. These systems often require camera calibration to achieve optimal accuracy, especially when intrinsic camera parameters are not readily available. Marker detection systems are commonly implemented using computer vision libraries that support robust tracking even in low light or partially obscured conditions [19, 20].

2.2. Guidance Systems and User Interaction

One of the most promising applications of AR is in the development of guidance systems, particularly for assembly tasks or step by step instructional procedures. These systems have shown effectiveness in improving task performance by reducing errors and enhancing user understanding [21]. AR based guidance can be implemented through various devices, such as Head Mounted Displays (HMDs) or handheld tablets and smartphones. HMDs provide an immersive experience by placing digital overlays directly into the user's field of vision, while handheld devices offer portability and intuitive interaction through touchscreens [22]. There are two types of HMDs commonly used: optical see through, which uses transparent displays to blend virtual objects into the real world, and video see through, which captures the environment through a camera and merges it with digital content. Each type offers different advantages in terms of realism, interaction, and comfort [23]. Studies have shown that AR can be effectively used in both industrial and non industrial assembly scenarios, such as constructing furniture or assembling modular components like building blocks. These systems may include interactive 3D models, animated instructions, and spatial indicators to guide users in real time [24]. In some configurations, AR systems are enhanced by gesture control or voice commands, offering hands free operation that improves user experience. The interaction design also varies depending on the device used. For handheld AR, interactions are typically executed via touchscreen buttons that control navigation between steps, update visual instructions, or display contextual information relevant to the task [25].

2.3. System Evaluation

To measure the effectiveness of AR guidance systems, both quantitative and qualitative evaluations are commonly conducted. Quantitative evaluation often includes task performance metrics such as completion time and error rates [26]. In addition, cognitive load assessments are used to determine how mentally and physically demanding a system is for users. One standard tool for this is a workload index that measures six categories including mental demand, physical demand, temporal demand, effort, perceived performance, and frustration [27]. These categories are typically evaluated using rating scales that reflect the user's perception after completing a task. Qualitative data is usually collected through post task questionnaires that inquire about user preferences, perceived ease of use, and any difficulties experienced during interaction. Demographic information such as age, prior experience with AR, or familiarity with similar tasks is also recorded to provide context to the findings [28]. Comparing different modalities, such as paper based instructions versus AR based systems, helps reveal not only which method offers better performance but also which one is preferred by users in practical scenarios. These evaluations contribute to understanding the usability and potential of AR as a support tool in guided operations, offering insights into how such systems can be refined and scaled for broader applications [29].

3. RESEARCH METHOD

This section presents the design and implementation of this work's methods. It explains more about AR applications with different designs for each device and details the evaluation used for this work [30].

3.1. System Design

The overall design is based on three essential components for this system: user device, 3D objects,mand placement area. For handheld AR, using the "ArUco" fiducial marker system, the marker will represent the location placement area and must be visible in the device's camera. HMD AR will use the device's features to understand real world rooms and position virtual objects [31].

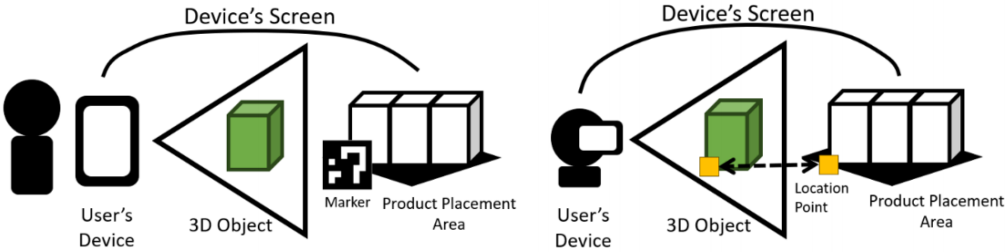

Figure 1. Illustration of the system for two types of AR devices: Handheld and wearable

As illustrated in Figure 1, the system starts by finding a suitable place to create 3D objects. Handheld and HMD devices handle this process differently, as illustrated in Figure 1, but both will begin under the user's input. If the process is in order and the user presses the "Start" button, the system will create translucent 3D objects over the set location on one of the partitions of the shelves [32]. These objects are representations of random procedural planograms as a guide for users to place products in the form of a stack of products, but these objects only show one of them on each step [33].

Additional information and interactable virtual buttons will be different on each device to use its strengths [34]. Users then try to place products inside 3D objects as closely as possible, and they need to be finished correctly before moving into the following stack [35]. Since the system doesn't have automatic correction, evaluators must watch the user's process, warn them when the error occurs upon placing products, and instruct them to fix the problem. These errors have specific conditions that must be met as critical. Otherwise, any other minor issues will not count, and the user will not be stopped [27]. When users place the current stack correctly, they press the virtual button to show the following stack and hide the current stack. Another virtual button functions to return to the previous stack and hide the current stack whenever users are caught having an error on the last stack but accidentally go to the following stack [36]. These steps will be repeated until all stacks are finished, thus ending the system. The system will show users that it has been finished afterward and its completion time. For evaluation purposes, the system will also have a restart function to make the system back from the start [37].

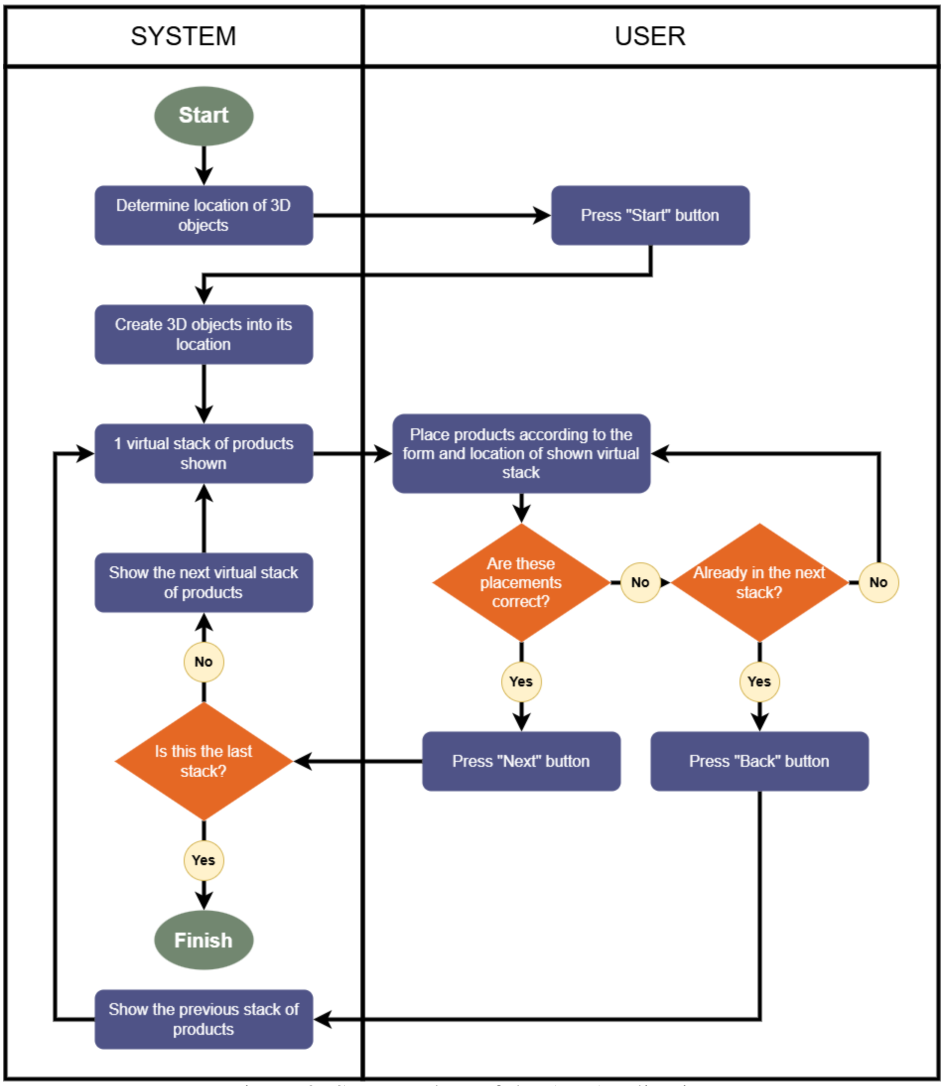

Figure 2. System Flow of the AR Application

As shown in Figure 2, the AR system guides users through the product placement process by displaying virtual product stacks step by step. The system determines the location of 3D objects, shows each stack sequentially, and allows returning to the previous stack if needed. The user starts the process, places products based on the displayed virtual reference, and uses the Next or Back buttons to confirm or correct placements. This flow ensures real time guidance while allowing users to adjust mistakes without restarting the entire task.

3.2. System Flow of the AR Application

The device for handheld system is Samsung Galaxy Tab S7 among other devices available. Upon further testing, it has been concluded that the device is big enough to detect markers while having 3D objects visible and small enough to be comfortable for holding with either hand. This application was made with the help from "OpenCV for Unity" extension's built in marker detection based on "ArUco" by [38, 39]. With handheld, based on few references [40, 41], users will interact the system with virtual buttons on the screen.

Figure 3. Different Sequences of AR System for Handheld

As illustrated in Figure 3, the system shows many sequences: when the system starts, when the user starts to place products, and when the system is finished. On the first part, users must find one or both of markers set up on the shelves, Reference source not found. using the device's camera. When the system detects them, the button to start the system will be interactable [42, 43]. When users are ready, they should press the interactable button, and the next screen will be available. On the second part, the system will show necessary information (such as the quantity of the products, name of products, and image of products) on the screen as well as buttons to continue into next stack or previous stack of products [44]. Users can press those buttons by touching inside an area of them on the screen. Users should rely on this additional information on the screen alongside 3D objects on the shelves for its location and position [45]. Lastly, the screen will show the indication that the system was finished as well as the completion time for the system as shown in the last part. The restart button will be used by evaluator for restarting the whole system so that it can be used for the next user [46]. For the implementation, the system has been developed using Unity version 2022.3.49f1 and using "OpenCV for Unity" extension to aid with the development of AR system for handheld. Both AR applications have been built into each own device independently [47].

3.3. HMD AR System Implementation

The device for the HMD system is Meta Quest 3, one of the widely available mixed reality (MX) headsets that allow people to see the world with a camera instead of a see through screen [48]. This device has room scanning features for apps to understand the surrounding room and makes virtual objects interact with the room more accurately. This data can be manipulated further by changing the size, position, and rotation of each of the 3D objects representing the room and objects inside it according to the user's preference [49]. For this work, the 3D object representing shelves got leveled down to the height of the partition used for placing products, as pictured in Figure 4.

In addition, Meta Quest 3 supports full passthrough mixed reality mode, enabling users to maintain spatial awareness while interacting with virtual product stacks in real time. This feature minimizes disorientation and allows users to clearly observe both the physical shelf and the overlaid 3D guidance elements simultaneously. The alignment process between the virtual shelf and the real world environment was performed through spatial anchors, ensuring that the 3D placement cues remain consistent even when the user moves around the workspace. Furthermore, gesture and controller based interactions were enabled to allow users to switch between product stacks, confirm placement steps, or adjust viewing angles without interrupting the workflow. This integration results in a more natural and immersive product placement experience, improving user adaptability and reducing cognitive load during task execution.

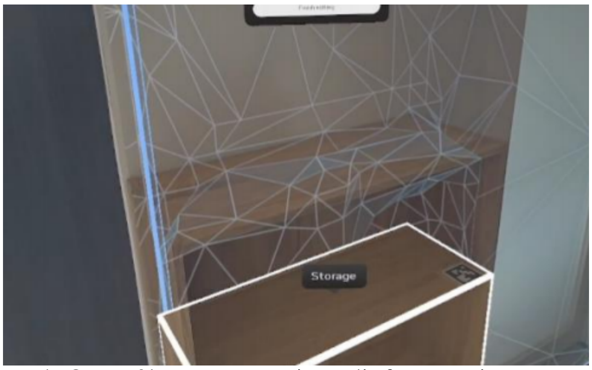

Figure 4. Quest 3's room scanning edit for experiment purpose

As shown in Figure 5, three parts correspond to the system work like the handheld system. In the first part, users can see a text box and an interactable virtual button on top of the shelves. When users are ready, they should press the start button to start the system [50]. In the second part, users will see additional information like the handheld system and two buttons to continue to the following stack and previous stack, respectively, in the same place as the earlier part. The button for continuing to the following stack has a cooldown time after pressing it to ensure that there will be no accidental press, as some internal testing has concluded that it is necessary [51]. Still, it only applies to the last stack of products since users can return to the previous stack on another order.

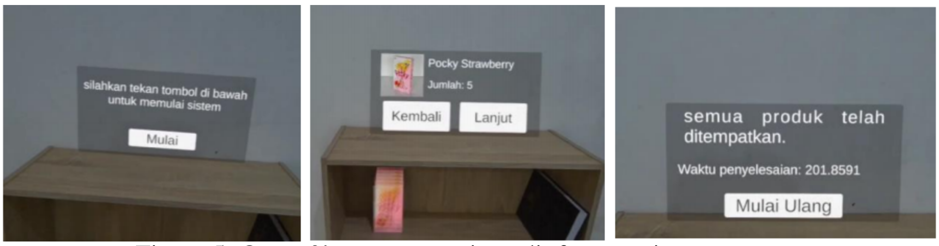

Figure 5. Quest 3's room scanning edit for experiment purpose

All buttons are interactable using real hands, but those only affect the user's pointing finger on both hands. The consideration of using real hands as a virtual object interaction method proved to be the most natural and most effortless for people to adapt through some internal testing [52]. When all stacks were placed, the text box like handheld system, as shown in the last part, was in the same place as other previous parts. It also had a similar restart button to the handheld system for the evaluator to restart it [53, 54].

3.4. Evaluation

Based on [55] with some modifications, all three scenarios: manual (paper), handheld AR, and HMD AR, will be evaluated through qualitative and quantitative measures. The evaluation framework combines task performance, error measurement, and cognitive workload assessment to ensure that both objective and subjective dimensions of user experience are captured. For the manual scenario in particular, the planogram format was designed based on the work by previous research but extended with additional information such as AR devices, so that participants can compare conventional and AR based approaches more directly, as illustrated in Figure 6. Quantitative evaluation includes recording completion time for product placement tasks and categorizing errors into product misplacement and location errors, while qualitative evaluation involves post test questionnaires to capture user perception, ease of use, and preference ranking. In addition, cognitive load is measured using a modified RTLX questionnaire to evaluate mental demand, physical demand, temporal demand, effort, perceived performance, and frustration levels after each scenario. This combination of measures ensures a comprehensive assessment that goes beyond efficiency alone, capturing how users adapt to AR interaction and how it compares with the traditional paper based planogram method.

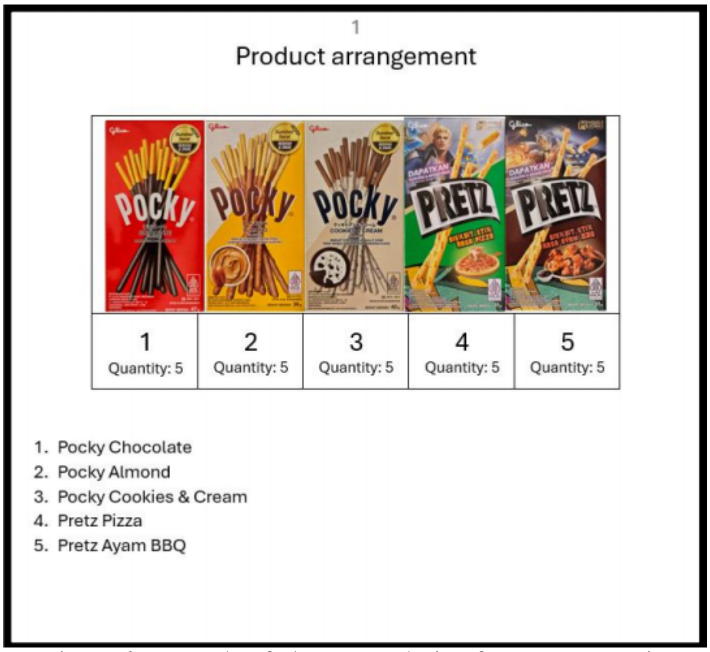

Figure 6. Example of planogram design for paper scenario

The products used for evaluation were based on real scenarios since users usually stack products of the same type or similar in dimensions, as pictured in Figure 7. There were only two types of products for the evaluation. Each had nine variants. For evaluation purposes, users always put five stacks of products and five products on each stack.


Figure 7. Example of Product Arrangements in a Supermarket

For quantitative measures, the time completion was based on the total time the user finished the work and the time needed to correct errors, since users must ensure everything is in order before continuing. For error measurement, it was categorized into two types, namely wrong product and wrong placement location (for example, when the arrangement was too far from the designated area). Placement error is counted when the user is about to move on to the next stack of products. This work used RTLX for cognitive load measurement with modified questions for each category in the local language for users. These questions will be given after the user finishes with each scenario. For qualitative measures, post test questionnaires will be given to users when they finish all the scenarios.

These questionnaires were slightly modified versions of, as shown in Table 1, and additional information such as age and gender.

Table 1. Post-Task Questionnaire for Evaluation

# Questions	Answer Type
Q1 Was the amount of information displayed/given appropriate?	Likert-type scale (1: lowest, 7: highest)
Q2 Were the given placement instructions difficult to understand?	Likert-type scale (1: lowest, 7: highest)
Q3 Order of methods (scenarios) according to preference.	Ordered List
Q4 What were the main difficulties in the experiment?	Descriptive
Q5 After the experiment, I had symptoms of. . .	Descriptive
Q6 Any suggestions you consider relevant to experiment?	Descriptive
Q7 Any additional comments you may consider relevant?	Descriptive

This work assigned 11 total participants as users for evaluation, and all of them were experienced in product placement and had never worn HMD before, with only one female among them. Participants were 31 on average, 19 years old at youngest and 47 years old at oldest. These participants were separated into groups, each for a session at a different time from the others, and each group had a maximum of 4 participants. These participants will work in the same room with the setup pictured in Figure 8. The room has enough light for the handheld AR's marker system to work consistently. Participants will place products from the starting box on the right side of the shelves.

To ensure consistency and fairness across trials, all participants were provided with identical initial instructions by the evaluator before the experiment began. The grouping strategy also minimized external influence, as no participant from one group had contact with those from another session prior to their turn. The room setting, as shown in the figure, was deliberately designed to replicate a realistic small scale retail environment, while maintaining controlled lighting conditions to avoid marker detection failure. The placement task was structured so that every participant interacted with the same product categories, ensuring comparability in results. Furthermore, the evaluator remained present during each session, observing both the interaction with the devices and the physical process of placing products, while ensuring that participants followed the same procedural steps in every scenario.

Figure 8. Evaluation Setup

All the participants were given instructions to work on the current scenario together before they worked on the evaluation individually in order afterward before continuing into the following scenario. This process will be repeated for each scenario until all are finished. The scenario order was as follows: manual, handheld, and HMD. To minimize the effect of learning by each participant, every scenario and participant will be given randomized product arrangements inside the starting box, a randomly generated planogram for AR devices, and different planogram paper for the manual scenarios. There were enough planogram papers for each of the participants. An evaluator monitored each participant with slightly different approaches to each scenario. For the manual scenario, the evaluator had to use a stopwatch that starts with participants picking up the paper until the participants finished placing the last stack of products correctly. For handheld AR scenarios, evaluators should try to watch the device's screen to judge if their placements were correct. The HMD AR scenario had a similar approach to handheld AR, but since the screens were inside HMD, screencasting was needed to see what HMD was looking at. Evaluators should watch the screencasts from other devices while monitoring participants directly. For both AR devices, time completion was recorded in the device. Therefore, the evaluator did not need an external stopwatch to track their completion time.

4. RESULT AND DISCUSSION

This section presents analyzed and processed results from conducting an evaluation using references that were used for research from [1], which was based on Exploratory Data Analysis (EDA) from [56], ANOVA from [57], nonparametric tests from Gibbons and Chakraborti, and Multivariate Analysis [58]. This combination of statistical techniques was chosen to ensure that both parametric and nonparametric aspects of the data could be properly assessed, and that the interpretation of findings would remain robust across different methodological perspectives.

4.1. Task Performance

The average completion times for manual, handheld AR, and HMD AR are 75.43s, 108.87s, and 103.02, respectively, with data representation as box plots illustrated in Figure 9. These values demonstrate clear performance gaps between methods, with manual consistently outperforming AR based approaches in terms of efficiency. The equality of three medians was tested with a nonparametric ANOVA using the Friedman test because the data normality was tested using the Shapiro Wilk method, proving that the data was not normally distributed. The Friedman test for completion time rejected the null hypothesis (p-value < 0.001), indicating significant differences between scenarios. These results suggest that although AR systems provide interactive guidance, they still require additional time for participants to adapt and operate, particularly for handheld devices where physical handling and screen interaction may add complexity compared to the directness of paper instructions.

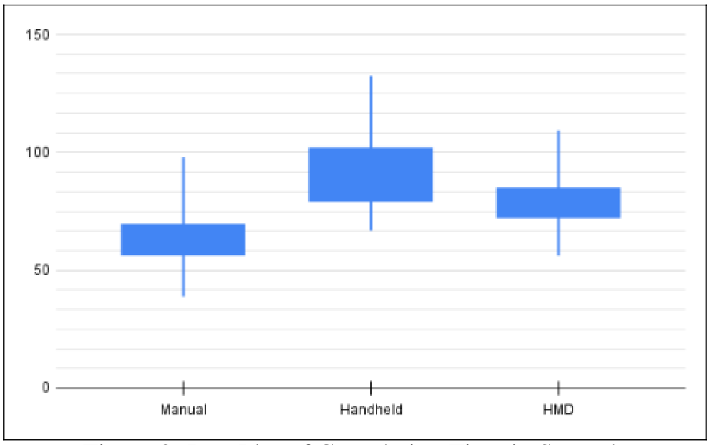

Figure 9. Box Plot of Completion Time in Seconds

The number of errors made by participants consisted of two product errors and three placement errors, and their contingency with the scenarios is shown in Table 2. Fisher Freeman Halton's exact (two-sided) test could not be finalized with a chi-squared test because the contingency table did not meet the assumptions required for chi-squared analysis. Therefore, it was concluded that there were no correlations between errors and scenarios.

Table 2. Contingency Table between Errors and Scenarios

Error/Scenario	Manual	Handheld	HMD
Product	2	0	0
Placement	0	3	0

Table 2 illustrates that product errors occurred only in the manual scenario, while placement errors appeared exclusively in the handheld scenario, with no errors recorded in the HMD condition.

4.2. Cognitive Load

RTLX, which consists of six categories mental demand, physical demand, temporal demand, effort, performance, and frustration level was used for cognitive load measurement with a 10 point Likert type scale. These results were compared across the three methods for each category. A nonparametric ANOVA using the Friedman test was applied because all participants performed all scenarios and the RTLX data were ordinal. Using $\alpha = 0.05$, the analysis showed that mental demand, temporal demand, effort, and frustration exhibited no significant differences between scenarios.

One of the categories that proved to have significant differences among scenarios was physical demand (p-value = 0.027). Furthermore, on pairwise comparisons between each scenario, only the handheld scenario had significant differences with HMD scenario (p-value = 0.02), as a comparison between handheld with manual proved it had no significant differences (p-value = 0.058), as well as HMD with manual (p-value = 1). Another category that had significant differences among scenarios was performance (p-value = 0.014). Furthermore, on pairwise comparison between comparisons between each scenario, only the handheld scenario had significant differences from the manual scenario (p-value = 0.003), as both comparisons between the handheld scenario with the HMD scenario and the manual scenario with the HMD scenario proved to have no significant differences with a p-value of 0.371 and 0.132 respectively.

4.3. Post-Test Preferences

Participants were given post test questionnaires after they finished up with all scenarios about opinions concerning the evaluation and their preferences. Participants preferred manual scenario the most (7 people), followed by AR using HMD (4 people). Based on the answers, the amount of information that was shown and given by the system was very adequate (6.09 in mean) and the instructions that had been given by the evaluator were easy enough to understand (1.64 in mean). Some participants made commentaries regarding evaluations, one of them was the problem with using HMD device. One of the participants said that using HMD made them dizzy, and some other participants said that the image was a little blurry, but not enough to make them dizzy. For handheld AR, some of the participants voiced their discomfort while holding the device while trying to place products because of how heavy the device was.

5. MANAGERIAL IMPLICATION

The findings of this study highlight that although manual methods remain the most efficient in terms of task completion time, AR based approaches such as handheld and HMD devices offer additional value for training, visualization, and long term innovation in merchandising. Managers should therefore evaluate technology adoption not only based on speed, but also on the potential to improve employee learning, customer engagement, and differentiation from competitors. In addition, the discomfort reported with handheld AR due to device weight and the dizziness experienced by some participants when using HMD devices underline the importance of considering ergonomics and user experience in managerial decisions. Retailers and technology developers are encouraged to collaborate in order to optimize device usability, reduce physical strain, and ensure that the integration of AR technologies does not hinder employee performance.

Finally, the study suggests that successful implementation of AR technologies in retail settings requires a gradual and adaptive approach. Managers should begin with pilot projects on a small scale, continuously collect user feedback, and iterate improvements before scaling up. This strategy will not only reduce risks but also align technology adoption with organizational readiness, employee capability, and customer expectations.

6. CONCLUSION

This work presents a comparison between conventional methods and AR devices as part of a user study on product placement. The results from the evaluation proved that using the manual scenario is still preferable to others in terms of efficiency and user acceptance. However, the findings also indicate that HMD has better potential compared to handheld AR, suggesting that future development of AR based merchandising solutions should prioritize immersive and ergonomic designs. Improvements for both AR implementations, particularly handheld, are necessary to enhance stability, usability, and overall performance.

From a practical perspective, these results emphasize that managers and practitioners should carefully consider the trade off between efficiency and innovation when adopting AR technologies. While manual approaches remain the most efficient, AR solutions provide added value in visualization, training, and long term digital transformation strategies. Enhancing marker based systems, refining device ergonomics, and designing interfaces that balance clarity with information density are promising directions for practical applications in retail. Nevertheless, this research faced limitations, particularly in the number of participants. Due to time constraints, the study involved only 11 participants, which may affect the generalizability of the findings.

Future research should involve a larger and more diverse sample of users to obtain stronger statistical evidence and enable deeper comparative analysis between AR and manual approaches. In addition, further studies could expand the evaluation scope by including longer product placement tasks, examining different AR hardware, and exploring the cognitive and ergonomic impacts over extended usage. As AR technology rapidly progresses, there will be more opportunities for stable, accurate, and user friendly implementations. Future studies are encouraged to leverage these technological advancements to design more effective AR systems that align with both employee needs and organizational goals, thereby advancing the role of AR in modern retail environments.

7. DECLARATIONS

7.1. About Authors

Nadhif Haikal Farhansyah (NH) https://orcid.org/0009-0001-2194-003X

Hadziq Fabroyir (HF) https://orcid.org/0000-0002-2529-1962

7.2. Author Contributions

Conceptualization: HF and NH; Methodology: NH; Software: HF; Validation: HF; Formal Analysis: NH, HF, and HF; Investigation: NH; Resources: HF; Data Curation: HF; Writing Original Draft Preparation: NH and HF; Writing Review and Editing: NH, HF, and NH; Visualization: HF; All authors, NH, and HF have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.4. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] J. B. Alves, B. Marques, C. Ferreira, P. Dias, and B. S. Santos, "Comparing augmented reality visualization methods for assembly procedures," *Virtual Reality*, pp. 1–14, 2022.

[2] T. Pujiati, H. Setiyowati, B. Rawat, N. P. L. Santoso, and M. G. Ilham, "Exploring the role of artificial intelligence in enhancing environmental health: Utaut2 analysis," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 37–46, 2025.

[3] V. Bondarenko, M. Attawna, G. T. Nguyen, and F. H. Fitzek, “Motion sickness comparison of 2 xr approaches: camera+ screen or hologram on transparent lens (meta quest 3 or microsoft hololens 2),” in *2024 International Electronics Symposium (IES)*. IEEE, 2024, pp. 728–733.

[4] M. H. R. Chakim, U. Rahardja, E. D. Astuti, E. Erika, and C. T. Hua, “The social empowerment role of the penta helix entrepreneurship ecosystem in driving the national economy,” *ADI Pengabdian Kepada Masyarakat*, vol. 6, no. 1, pp. 1–13, 2025.

[5] I. Sasono and M. Aman, “Framework of master data management in banking using consolidation and jaro winkler algorithm,” *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 2, pp. 186–197, 2025.

[6] M. Drouot, N. Le Bigot, E. Bricard, J.-L. De Bougrenet, and V. Nourrit, “Augmented reality on industrial assembly line: Impact on effectiveness and mental workload,” *Applied Ergonomics*, vol. 103, p. 103793, 2022.

[7] S. Lestari, S. Watini, and D. E. Rose, “Impact of self-efficacy and work discipline on employee performance in sociopreneur initiatives,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 2, pp. 270–284, 2024.

[8] V. Havard, D. Baudry, B. Jeanne, A. Louis, and X. Savatier, “A use case study comparing augmented reality (ar) and electronic document-based maintenance instructions considering tasks complexity and operator competency level,” *Virtual Reality*, pp. 1–16, 2021.

[9] V. Agarwal, S. Verma, A. Bist, U. Rahardja, and P. K. Goel, “Natural language processing (nlp) for policy recommendations in carbon management,” in *Advanced Systems for Monitoring Carbon Sequestration*. IGI Global Scientific Publishing, 2025, pp. 357–374.

[10] M. Stoica, “The role of technological innovationin merchandising,” *Three Seas Economic Journal*, no. 4, pp. 19–27, 2023.

[11] A. I. Zulkarnain, N. A. Achsani, M. Siregar, and I. S. Beik, “Enhancing accountability in hajj fund governance through regulatory impact analysis and value chain model,” *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 5, no. 2, pp. 198–213, 2025.

[12] T. Kitsukawa, M. Takahashi, A. Moro, Y. Harada, H. Nishikawa, M. Noguchi, A. Hamaya, and K. Umeda, “A recognition system of ar markers attached to carts in a factory,” in *2022 IEEE/SICE International Symposium on System Integration (SII)*. IEEE, 2022, pp. 608–613.

[13] N. Leins, J. Gonnermann-Müller, and M. Teichmann, “Comparing head-mounted and handheld augmented reality for guided assembly,” *Journal on Multimodal User Interfaces*, vol. 18, no. 4, pp. 313–328, 2024.

[14] M. Asri, M. Hardini, D. Apriliasari, U. Rahardja *et al.*, “Influence of technology adoption and internet security on satisfaction and investment decision quality,” in *2024 Ninth International Conference on Informatics and Computing (ICIC)*. IEEE, 2024, pp. 1–6.

[15] B. R. Maran, L. Giridharan, and R. Krishnaveni, “Augmented reality-based indoor navigation using unity engine,” in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*. IEEE, 2023, pp. 1696–1700.

[16] L. Xue, “Designing effective augmented reality platforms to enhance the consumer shopping experiences,” Ph.D. dissertation, Loughborough University, 2022.

[17] A. H. Aditiya, H. Hamdan, S. N. W. Putra, S. Visiana, and R. Thakkar, “Transforming education with genai: Case study on chatgpt, midjourney, and policy changes,” *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 20–27, 2025.

[18] L. Marinelli, F. Fiano, G. L. Gregori, and L. M. Daniele, “Food purchasing behaviour at automatic vending machines: the role of planograms and shopping time,” *British Food Journal*, vol. 123, no. 5, pp. 1821–1836, 2021.

[19] M. Saqlain, S. Rubab, M. M. Khan, N. Ali, and S. Ali, “Hybrid approach for shelf monitoring and planogram compliance (hyb-smpc) in retails using deep learning and computer vision,” *Mathematical Problems in Engineering*, vol. 2022, no. 1, p. 4916818, 2022.

[20] Y. Song, J. Qin, L. Dong, and Y. Zhao, “Design of mobile augmented reality system based on slam,” in *2021 International Conference on Culture-oriented Science & Technology (ICCST)*. IEEE, 2021, pp. 43–46.

[21] O. Jayanagara and D. S. S. Wuisan, “An overview of concepts, applications, difficulties, unresolved issues in fog computing and machine learning,” *International Transactions on Artificial Intelligence*, vol. 1,

no. 2, pp. 213–229, 2023.
[22] S. A. Umezurike, O. V. Akinrinoye, O. T. Kufile, A. Y. Onifade, B. O. Otokiti, and O. G. Ejike, "Augmented reality shopping experiences: A review of retail immersion technologies and outcomes," *International Journal of Management and Organizational Research*, vol. 3, no. 2, pp. 83–94, 2024.
[23] Y. Yan, X. Bai, W. He, S. Wang, X. Zhang, P. Wang, L. Liu, and Q. Yu, "A novel adaptive visualization method based on user intention in ar manual assembly," *The International Journal of Advanced Manufacturing Technology*, vol. 129, no. 9, pp. 4705–4730, 2023.
[24] B. E. Sibarani, C. Anggreani, B. Artasya, and D. A. P. Harahap, "Unraveling the impact of self-efficacy, computer anxiety, trait anxiety, and cognitive distortions on learning mind your own business: The student perspective," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 1, pp. 29–40, 2024.
[25] A. Felix, D. Y. Bernanda, A. S. Kembau, F. Effendy, and R. Nathaniel, "Application-based elementary schools interactive education platform analysis and design," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 2, pp. 114–128, 2025.
[26] M. E. Yücel and C. Ünsalan, "Planogram compliance control via object detection, sequence alignment, and focused iterative search," *Multimedia Tools and Applications*, vol. 83, no. 8, pp. 24 815–24 839, 2024.
[27] S. R. Billewar, K. Jadhav, V. Sriram, D. A. Arun, S. Mohd Abdul, K. Gulati, and D. N. K. K. Bhasin, "The rise of 3d e-commerce: the online shopping gets real with virtual reality and augmented reality during covid-19," *World Journal of Engineering*, vol. 19, no. 2, pp. 244–253, 2022.
[28] B. Rawat, N. Mehra, A. S. Bist, M. Yusup, and Y. P. A. Sanjaya, "Quantum computing and ai: Impacts & possibilities," *ADI Journal on Recent Innovation*, vol. 3, no. 2, pp. 202–207, 2022.
[29] D. Gathmyr, U. Suhud, H. Herlitah, H. Hamidah, R. T. H. Safariningsih, and J. Wilson, "Technological advancements in perceived organizational support enhancing healthcare systems towards sustainable development goals," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 516–526, 2025.
[30] T. Zigart and S. Schlund, "Ready for industrial use? a user study of spatial augmented reality in industrial assembly," in *2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*. IEEE, 2022, pp. 60–65.
[31] M. Rakhmansyah, M. S. Hadi, S. R. P. Junaedi, F. A. Ramahdan, and S. N. W. Putra, "Integrating blockchain and ai in business operations to enhance transparency and efficiency within decentralized ecosystems," *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 157–167, 2025.
[32] B. Berman and D. Pollack, "Strategies for the successful implementation of augmented reality," *Business Horizons*, vol. 64, no. 5, pp. 621–630, 2021.
[33] T. Emrich, *The Next Dimension: How to Use Augmented Reality for Business Growth in the Era of Spatial Computing*. John Wiley & Sons, 2024.
[34] D. S. S. Wuisan, R. A. Sunardjo, Q. Aini, N. A. Yusuf, and U. Rahardja, "Integrating artificial intelligence in human resource management: A smartpls approach for entrepreneurial success," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 3, pp. 334–345, 2023.
[35] M. Ruocco, P. Saeghe, F. Kerber, J. Gugenheimer, M. McGill, and M. Khamis, "From redirected navigation to forced attention: Uncovering manipulative and deceptive designs in augmented reality through retail shopping," in *2024 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, 2024, pp. 720–729.
[36] K. Yücel and C. Ünsalan, "Automatic planogram compliance checking using deep learning-based object detection," *Journal of Real-Time Image Processing*, vol. 21, no. 3, pp. 541–556, 2024.
[37] D. Leone, M. C. Pietronudo, and L. Dezi, "Improving business models through augmented reality applications: evidence from history, theory, and practice," *International Journal of Quality and Innovation*, vol. 6, no. 1, pp. 28–42, 2022.
[38] S. Garrido-Jurado, J. Garrido, D. Jurado-Rodríguez, F. Vázquez, and R. Muñoz-Salinas, "Reflection-aware generation and identification of square marker dictionaries," *Sensors*, vol. 22, no. 21, p. 8548, 2022.
[39] D. Jurado-Rodríguez, R. Muñoz-Salinas, S. Garrido-Jurado, and R. Medina-Carnicer, "Planar fiducial markers: a comparative study," *Virtual Reality*, 2023.
[40] J. B. Alves, P. Silva, and A. Duarte, "Evaluating interaction techniques in augmented reality environments for training scenarios," in *Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, 2022, pp. 450–459.
[41] J. Leins, P. Schneider, and M. Fuchs, "Handheld augmented reality for industrial training: A usability

study," *Journal of Industrial Information Integration*, vol. 35, p. 101730, 2024.

[42] T. Maran, C. Bogdan, and M. Klein, "Augmented reality in retail: Enhancing consumer product interaction," *Computers in Human Behavior*, vol. 138, p. 107515, 2023.

[43] M. Zigart and S. Schlund, "Exploring user interfaces for mobile augmented reality in logistics," in *Proceedings of the 2022 ACM Conference on Human Factors in Computing Systems (CHI '22)*, 2022, pp. 1–12.

[44] Z. S. Kabir and K. Kang, "An interaction–engagement–intention model: How artificial intelligence and augmented reality transform the user–platform interaction paradigm," *Electronics*, vol. 14, no. 12, p. 2499, 2025.

[45] M. Deshpande, B. Likhita, and N. Bhat, "A personalized supermarket product recommendation system using augmented reality," *ECS Transactions*, vol. 107, no. 1, p. 915, 2022.

[46] N. Ramadhona, A. A. Putri, and D. S. S. Wuisan, "Students' opinions of the use of quipper school as an online learning platform for teaching english," *International Transactions on Education Technology (ITEE)*, vol. 1, no. 1, pp. 35–41, 2022.

[47] M. Datta and R. Raman, "Ai and ml in retail: Iot sensors and augmented reality for competitive strategies using iot and linear regression," in *2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*. IEEE, 2024, pp. 1–5.

[48] R. Haris, S. Duygulu, A. Hafidah, R. Syakur, B. Djatmiko, A. Maryam, and A. Indrawati, "Enhancing ecopreneurship competency through bidan elok e-learning based on local wisdom," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 424–440, 2025.

[49] J. Liu, I. Huang, A. Anand, P.-H. Chang, and Y. Huang, "Digital twin in retail: An ai-driven multi-modal approach for real-time product recognition and 3d store reconstruction," in *2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. IEEE, 2024, pp. 368–373.

[50] R. Zimmermann, D. Mora, D. Cirqueira, M. Helfert, M. Bezbradica, D. Werth, W. J. Weitzl, R. Riedl, and A. Auinger, "Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalized recommendations and explainable artificial intelligence," *Journal of Research in Interactive Marketing*, vol. 17, no. 2, pp. 273–298, 2023.

[51] G. Chodak, "Augmented reality in e-commerce," in *The Future of E-commerce: Innovations and Developments*. Springer, 2024, pp. 147–167.

[52] R. Widayanti, M. H. R. Chakim, C. Lukita, U. Rahardja, and N. Lutfiani, "Improving recommender systems using hybrid techniques of collaborative filtering and content-based filtering," *Journal of Applied Data Sciences*, vol. 4, no. 3, pp. 289–302, 2023.

[53] A. Rizky, R. W. Nugroho, W. Sejati, O. Sy *et al.*, "Optimizing blockchain digital signature security in driving innovation and sustainable infrastructure," *Blockchain Frontier Technology*, vol. 4, no. 2, pp. 183–192, 2025.

[54] M. D. Devanesan and R. Venkatesh, "Impact of in-store retail technologies on enhancing retail footfall among physical retail formats in india," *Academy of Marketing Studies Journal*, vol. 25, no. 6, pp. 1–13, 2021.

[55] R. Aprianto, R. Haris, A. Williams, H. Agustian, and N. Aptwell, "Social influence on ai-driven air quality monitoring adoption: Smartpls analysis," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 28–36, 2025.

[56] A. Stuart, *Exploratory Data Analysis in the Behavioral Sciences*. New York: Routledge, 2022.

[57] B. G. Tabachnick and L. S. Fidell, *Using Multivariate Statistics*, 8th ed. Boston: Pearson, 2023.

[58] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 9th ed. Boston: Cengage Learning, 2024.