INTEGRATING AI INNOVATION AND RETAIL OPERATIONS: A TAM APPROACH TO PLANOGRAM COMPLIANCE

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ABSTRACT

In retail, planograms can have a significant impact on a customer's experience and a company's bottom line. For retailers, well-designed planograms can help to increase sales and improve inventory management, while customers benefit from things like an enhanced shopping experience and easier decision-making. Given the dynamics of the retail environment, one of the major issues with planograms is compliance. One of the major challenges with store level compliance is being able to visualize the store shelves to determine the state of compliance. Traditionally, retailers have relied on human judgment and labor to perform the planogram compliance tasks, resulting in lost sales, out-of-stocks and data errors. Recently, there have been technological advancements in artificial intelligence that can help to significantly improve planogram compliance. Through the lens of the technology acceptance model, this paper utilized a literature review to assess the likelihood of retailers adopting artificial intelligence tools for planogram compliance. After a thorough review of the literature, there appears to be a high likelihood of retailers adopting artificial intelligence tools, as these tools can help to revolutionize planogram compliance with an easier audit process, more accurate data, reduced labor costs and improved customer satisfaction.

Keywords: Planograms, Planogram Compliance, Artificial Intelligence, Generative Artificial Intelligence, Deep Learning

INTRODUCTION

In retail, planograms can have a significant impact on a customer's experience and a company's bottom line. Effective planograms can help retailers increase sales and improve inventory management, while customers benefit from things like an enhanced shopping experience and easier decision-making. Given the highly dynamic retail environment, one of the key issues with planograms is compliance. Without planogram compliance, maximizing the benefits from its use may be difficult to achieve. The retail environment can be complex, as it is filled with market nuances, rapid product rotation and unforeseen challenges. These realities can make it more challenging to ensure that retail stores are complying with the requirements of the planogram. One of the major challenges with store level compliance is being able to visualize the store shelves to determine the state of compliance. Traditionally, retailers have relied heavily on human judgment and labor in planogramming, which has often led to lost sales, out-of-stocks, and increased expenses (Sadayappan and Kumar, 2021). While companies use technology with hand-held computers, cameras and the internet, the labor-intensive process is prone to data errors. There is general agreement among scholars that incorporating modern technological advancements can help to improve compliance and lead to a process that is more effective and efficient. Recently, there have been significant technological advancements in artificial intelligence that can help to revolutionize and improve planogram compliance. Through the lens of the technology acceptance

model, this paper utilizes a literature review to provide a thoughtful perspective on planograms, the dynamics of planogram compliance, the likelihood of retailers adopting new artificial intelligence tools and the potential impact that artificial intelligence can have on planogram compliance.

THEORETICAL FRAMEWORK

To better understand the likelihood of retailers adopting artificial intelligence (AI) to assist with planogram compliance, this research will use the technology acceptance model (TAM) as the theoretical framework. This framework was developed in 1989 by Fred Davis when he wrote an article titled, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology", which began a discussion on how an individual's perceptions impacted use and acceptance of technology (Davis, 1989). In this article, Davis (1989) argues that a person's perceptions regarding how easy the technology is to use and whether or not the technology is useful will shape an individual's intention to adopt and subsequently use a new technology. The foundation of TAM came from the theory of reasoned action, which was developed by psychologists Martin Fishbein and Icek Ajzen in 1975 as an improvement to the information integration theory (Fishbein and Ajzen, 1975). The theory of reasoned action is a psychological model that helps to explain how attitudes and norms will influence a person's intention to perform a task and posits that a person's intention to act is the best predictor of whether they will actually perform the behavior (Davis et al., 1989). Davis extended this theory and applied it to technology by arguing that an individual's likelihood to adopt a new technology is driven by two perceptions, perceived usefulness and perceived ease of use. Perceived usefulness (PU) refers to the belief that the technology will help to improve job performance, while perceived ease of use (PEOU) refers to the belief that the new technology will be easy to use. Davis (1989) posits that these perceptions shape a person's intention to use the technology and can help to predict whether or not a new technology will be adopted. TAM has been validated and employed in many areas beyond technology including studies on healthcare, autonomous vehicles, e-learning platforms and e-business systems (Alshammari and Alkhwaldi, 2025). King and He (2006) conducted a meta-analysis of TAM, which included 88 published studies and found it to be a valid and robust model with the potential for much wider applicability. Later, Doulani (2018) conducted research that analyzed 164 studies and found that the core TAM variables of PU and PEOU continued to be strong measures and ideal constructs in the field.

While TAM is a highly useful theory, there are some criticisms regarding the lack of social and cognitive constructs. Venkatesh and Davis (2000) conducted a study with 156 participants at 4 different organizations, that extended TAM to include social influences and cognitive instrumental processes. They found that PU accounted for 40%-60% of the variation and 34%-52% of the variation in usage intentions, but that other social factors like subject norms, voluntariness and image and cognitive factors like job relevance, output quality, results demonstrability, and PEOU also have significant influence. This was a hallmark study and validated the extension of TAM2. Given the popularity and impact of TAM and TAM2, there was another extension. This extension is called TAM3 and focuses on further exploring PEOU. Venkatesh and Bala (2008) extended TAM2 by adding a set of determinants for PEOU, which included computer self-efficacy, perceptions of external control, computer anxiety, computer playfulness, perceived enjoyment, objective usability. However, TAM3 has been criticized for its complexity and lack of relevant research validating its effectiveness (Huang and Yang, 2025).

This study with utilize TAM and TAM2, but without the social influence variables. That is because the social influences variables include subject norms, voluntariness and image. While important, social influences are less relevant than the cognitive internal processes with regard to the potential of retailers adopting AI tools to better manage planogram compliance. As such, the cognitive processes of job relevance, output quality and results demonstrability are included in this evaluation.

METHODS

The purpose of this article is to investigate the likelihood of retailers adopting AI tools for the purposes of improving planogram compliance. Due to the lack of research regarding planogram compliance and AI, a structured literature review was used as the basis for this study. This approach allows for a synthesis of existing literature since the research is fragmented across these disciplines. This literature review can help to serve as a precursor to empirical research by helping to establish the relationship and impact between AI and planogram compliance. In addition, it can also highlight possible areas of future research.

The search for relevant articles spanned across several databases including Scopus, Web of Science, ABI/Form, Google Scholar, and Research Gate. The types of evidence included empirical studies, articles with relevant theoretical frameworks, peer-reviewed journal articles, conference proceedings, technical perspectives from industry experts and industry reports. These data were limited to research that was written in English and published between 2006-2025. To ensure a thorough search and review of the literature, the search focused on relevant key words regarding planogram compliance and AI. For planograms, the key words included planograms, planogram compliance, retail shelf management, shelf management at retail and challenges with planograms. For AI, the focus was on the current technology and automation used in planogram compliance and retail shelf monitoring, research that was focused on AI imaging and the emerging role of AI in retail operations. These key words included artificial intelligence, generative artificial intelligence, deep learning and machine learning. These terms were used in various combinations and refined to ensure a comprehensive review of the literature in planogram research, emerging technologies in planograms, and AI in the retail environment. There was also a significant focus on the intersection of planograms and AI, which was limited due to the emergence of this area of study.

The identification of articles included a 4-step iterative process. First, databases were searched for information and research. Once research was identified, a review of the abstract and/or overview was screened for potential relevancy. Once an article made it through the screening process, it was assessed via a full-text review. If an article was deemed relevant and useful, it was included in the literature review. Research that was seemingly related, but not relevant was excluded. Some examples include articles that focused explicitly on consumers, online retail, e-commerce, or retail operations not related to planograms. Additionally, research was excluded if the data was opinionated, lacked methodological transparency, or was from a non-credible source.

LITERATURE REVIEW

The following discussion provides a review of the literature regarding the likelihood of retailers adopting AI tools and the potential impact that it can have on planogram compliance. This

evaluation is done through the lens of TAM and TAM2 framework. As noted earlier, these theories argue that PE, PEOU, job relevance, output quality and demonstrable results are predictive and can help to determine the likelihood of adopting a technology. While there is limited research on planogram compliance through the lens of this theoretical framework, it appears to be particularly relevant for its ability to provide insight into adopting technologies across a variety of industries. To begin this review, the upcoming dialogue will explore the definition of planograms, the importance of planogram compliance at retail, key challenges with planogram compliance, relevant new AI tools and how these AI tools can help to improve planogram compliance.

Planograms and Compliance

In the retail environment, there can be significant variation among stores within the same chain. This variation can make it challenging to manage inventory, forecast product needs and provide effective shelf management. However, planograms can help to manage this variation by ensuring that products are in the ideal location on the shelf and that there is appropriate and consistent merchandising to help drive sales. Marder et al. (2015) support this notion and suggest that strategically optimized planograms are instrumental in enhancing sales and overall profitability.

Planograms are primarily used in the retail industry to help manage products on the shelves and standardize visual merchandising in retail store outlets. That is because major retailers like Walmart, CVS, Walgreens, Kroger and others have thousands of stores across the United States (US), which makes planograms even more important. According to the National Retail Federation (2023), in 2022, there were 4.2 million US retail stores with the top 10 retailers having more than 35,000 store fronts across the country. Given the sheer number of store fronts among top US retailers, it is important for them to have well-designed planograms if these companies expect to continue to grow and maximize sales. Retail stores can have a lot of variation due to things like store size, product trends, differences in product sell through, dynamic customer needs and geography. Additionally, there is further complexity due to the constant in-store shelf rotation of removing non-performing products and replacing them with new ones. To help deal with the variation and complexity at the store level, many retailers will use planograms. Planograms visualize the predefined ideal arrangement of products, where each product should be on the shelf and how many facings each product should have (Czerniachowska et al., 2021; Goel and Sharma, 2020; Laitala and Ruotsalainen, 2023; Marinelli et al., 2021; Saqlain et al., 2022). Czerniachowska et al. (2021) note that available shelf space is a limited resource in most local retail stores so having a planogram to follow helps retailers achieve desired sales. Ideally, planograms help to ensure that the right product is in the right place at the right time to maximize sales (Wiles et al., 2013). Marinelli et al. (2021) contend that a planogram allows retailers to use product categories to present products in an organized manner, which can help to increase sales. Furthermore, Marinelli et al. (2021) remind us that visual merchandising is the presentation of products in the best possible way to help retailers get a consumer's attention, which is a key aspect to increasing store traffic and sales. Goel and Sharma (2020) posit that planograms are useful at the point of sale, as they can lead to improved store layout/design and better space utilization, as it demonstrates the exact positioning of products. Similarly, the research supports the effectiveness of using planograms at retail. Mondol et al. (2021) conducted a study on visual merchandising with 365 respondents in fashion stores with the results showing a positive and significant relationship between store layout and a consumer's willingness to purchase. Lees (2024) notes a 2020 study by Visual Merchandising and Store Design that showed 73% of customers say good visual merchandising

makes them more likely to return. According to Lees (2024), customers are likely to spend 20% more time in stores with well-designed visual merchandising.

Using planograms can be a critical aspect to success in the retail environment. However, it all hinges on compliance. Chong et al. (2016) note this point and suggest that planograms are models that specify exactly how products should be displayed on the shelves to ensure maximum sales, while planogram compliance ensures that the products on display are in accordance with the planogram. For retailers to realize the benefits of having a well-designed planogram, it is necessary to have store level compliance, which ensures that the products on the shelf at the retail store match the desired arrangement in the planogram (Laitala and Ruotsalainen, 2023). For retailers, one of the most critical aspects of planogram compliance is the potential impact on sales. Saqlain et al. (2022) contend that monitoring store shelves to keep track of product availability and planned merchandising are crucial factors that can help to boost sales and improve customer satisfaction. Czerniachowska et al. (2021) agree and note that compliance can help retailers to maximize sales. The research supports this notion as well. A study by the National Association for Retailing Merchandising Services (as cited by Frontoni et al., 2015) found that 100% planogram compliance after an initial reset can help increase sales by 7.8%. Similarly, Saqlain et al. (2022) found that following an optimal planogram can amplify sales more than 7%. Laitala and Ruotsalainen (2023) agree but note that suboptimal merchandising can lead to a loss of up to 1% of sales. It is not only important for retailers to develop a planogram, but every effort also needs to be made to ensure that the retail store shelves are in compliance so the benefits can be realized. That being said, with many retailers having thousands of retail stores, ensuring compliance is an essential, but daunting task.

Key Challenges with Planogram Compliance

While there are well-established tools and software to develop planograms, there continue to be retail level concerns with planogram compliance. That is because compliance is more complicated than it may seem on the surface. For the most part, the current approach is labor-intensive, time-consuming and prone to human errors (Pietrini et al., 2024). The following discussion delves into these challenges that include a mostly manual process that lacks effective technology, which results in a costly, less desirable process that is prone to human errors.

Manual Process

One of the main challenges with planogram compliance is that the process for evaluating compliance tends to be a manually driven process. For decades, shelf monitoring has been carried out manually where qualified field workers periodically visit the store and manually scan and measure products (Pietrini et al., 2024). This process not only lacks efficiency, but also effectiveness, as the timing of these checks is not systematic, nor are the compliance checks linked to product rotations or seasonal fluctuations. Sadayappan and Kumar (2021) explain how problematic this approach is by noting that it often results in lost sales, late responses, more out-of-stocks, increased product waste and higher costs. Importantly, Melek et al. (2023) point out that an approach that goes beyond the traditional methods is needed to solve many of the problems associated with the lack of planogram compliance, including out-of-stocks, lack of effective shelf management and poor customer experience. Pietrini et al. (2024) agree and note that many retailers and brands are actively seeking automated solutions to improve this process.

Faulty Technology

While retailers use some technology for planogram compliance, it lacks effectiveness and is wrought with challenges. Saqlain et al. (2022) argue that improved technology is necessary for effective planogram compliance and optimized retail management. Computer vision is the key technology used in shelf management, but it continues to lack the necessary upgrades to be effective. Pietrini et al. (2024) posit that computer vision has made significant progress in identifying products at retail, but that it is still considered a challenging task from a computer vision perspective. While computer vision technology is available, the planogram compliance process continues to be faulty, as it relies on older equipment and requires human intervention to be completed. Specifically, human intervention is needed to take a picture of the shelf, determine if there are inconsistencies and then report back the results. Saqlain et al. (2022) posited that to automate this process, object detection of the products on the shelves can help to solve the problem of monitoring distinct categories and subcategories of products, assessing whether there are missing products and matching planograms continuously. However, currently, there are some problems with imaging and object detection that need to be improved to make the process more reliable. Many problems associated with object imagery for products on store shelves are linked to packaging with nuanced differences. This is a pretty significant challenge to address, as new products are introduced daily, product packaging is updated often and different varieties of the same product make it more difficult for product detection software to correctly identify and distinguish between products (Pietrini et al., 2024).

Data Errors

The reliance on a mostly manual process and faulty technology leads to another challenge with planogram compliance, which is that the data often has errors. It is labor-intensive and more likely to have errors. When employees are conducting compliance procedures manually, they need to go down each aisle in a store, look at each shelf and compare the products on the shelf to a visualization of the planogram, which is a process that can be prone to mistakes (Melek et al., 2023). Similarly, Sadayappan and Kumar (2021) agree and suggest that, traditionally, many retailers rely heavily on exploratory methods and human judgment to perform a planogram product assessment. Laitala and Ruotsalainen (2023) also agree and posit that the possibility of human error is always present with people conducting the compliance process. Many scholars agree that planogram compliance needs to move away from the traditional manual process and begin to incorporate more effective computer vision and object detection technology.

Due to the lack of modern technology, many retailers continue to be challenged with effectively managing compliance and are not fully realizing the benefits of having planograms. Using modern technological advancements can go a long way towards helping to improve planogram compliance, increase sales and reduce data errors. While this task has been challenging in the past, fast-paced technological advancements have given hope to new opportunities in planogram compliance. Like many other industries, these advancements are linked to AI. Up next, the focus will shift to AI tools and how these technological advancements can impact planogram compliance.

Artificial Intelligence and Planogram Compliance

Planogram compliance is essential to driving sales, improving store-level accountability and improving customer satisfaction in the retail environment. The traditional approach to compliance is labor-intensive, prone to mistakes and can benefit from impactful technologies (Popli, 2024). Retailers have begun to realize that the traditional approach of performing planogram product detections has its limitations and needs to be reimagined (Sadayappan and Kumar, 2021). While the more progressive retailers have begun to use AI, but for planogram compliance (Sadayappan and Kumar, 2021), it is far from an industry standard. As noted above, planograms are effective at providing a visual guide on how to display products in the retail environment, but there continue to be problems with compliance that can be significantly improved by incorporating AI into the process. The following discussion provides insight into how incorporating AI into planogram compliance can positively impact retailers.

It is important to understand the process for visualizing the store shelf, which is detailed in the five-stage planogram compliance framework. Early shelf-space optimization models, such as Corstjens and Doyle (1981), established these specification stages. With the development of computer vision, planogram checking became an image analysis task (Tonioni et al., 2017), resulting in automated detection, classification and metric-based compliance scoring (Hübner and Kuhn, 2012). The previous literature on shelf-space reallocation optimization (Hwang et al., 2005) inspired the correction stage, which was later unified under the modern AI-planogram framework. The Planogram Compliance Framework (Figure 1) details the typical process for collecting planogram compliance data, serving as a conceptual roadmap that links retail operations, AI-driven analytics and ethical governance into a continuous improvement cycle. Beginning with planogram specification, the framework proceeds through image capture, detection and classification, compliance scoring and correction. Each stage represents a distinct function, from defining ideal shelf arrangements to using deep learning algorithms for product recognition and generative AI models for layout correction.

Figure 1. Planogram Compliance Framework

PLANOGRAM COMPLIANCE FRAMEWORK
FIGURE 1

Specification Phase - Defines ideal shelf layouts for stores to maximize sales and ensure organized merchandise presentation.

Image Capture - Shelf photos are collected as the basis for automated analysis and compliance verification.

Detection and Classification - Algorithms accurately identify products and sort them according to the planogram requirements.

Compliance Scoring and Correction - Scores adherence to the planogram and initiates corrections to fix any discrepancies found.

Integrating AI into planogram compliance can help to transform how stores manage space and inventory. That is because AI is a powerful tool that has already begun to revolutionize the planogram compliance process, as recent developments have impacted every part of the five-stage planogram compliance framework. Chong et al. (2016) examined various types of training images to determine which are most suitable for achieving product image classification on retail store shelves and found that training on a mix of images from the internet and retail stores outperformed the other models. Likewise, AI tools can photograph in-store assortments to identify variations by comparing in-store shelves to planograms, which can then fully reach planogram compliance (Taylor, 2023). Furthering this discourse, Sadayappan and Kumar (2021) underscored the transformative application of using AI to refine retail planograms, as they can help to better rank and recommend products, gain data-driven insights, improve customer satisfaction and enhance sales.

One area that has driven advancements in this area include deep learning (DL), which has emerged as a powerful tool for planogram compliance and retail product detection, as it offers significant improvements in efficiency and accuracy. It was first introduced in 2006 as research on pattern recognition (Hinton et al., 2006) and has been instrumental in retail. It displayed improved performance metrics, as it can automatically learn features from images, such as those used in computer visualization and planogram compliance (Saqlain et al., 2022). However, some challenges with DL include high resource demands and adaptability issues, as it requires a large amount of annotated data for training and flexibility issues. Convolutional neural networks (CNNs), a subset of deep learning, has been at the heart of the enhanced image-based compliance and product detection improvements that are helping to overcome challenges in differentiating between products with similar packaging and sizing. CNN algorithms take in an image, assign importance to various objects and differentiate among them (Saha, 2018). CNNs have achieved remarkable performance on image classification tasks, leading to more accurate results (Goel and Sharma, 2020). Higa and Iwamoto (2019) conducted a study that used supervised learning to improve on shelf availability. The authors focused on ensuring high shelf availability by using CNNs to observe the changes in shelf regions. Their experiments achieved a success rate of 89.6% for product availability, which was much higher than that of traditional methods. Recently, Laitala and Ruotsalainen (2023) used CNNs for retail product detection where products were detected and classified, then compared to planograms to evaluate compliance. Their method provided an improved planogram compliance evaluation pipeline with accurate product location estimations. In the compliance scoring stage, Yucel et al. (2022) modified the Needleman-Wunsch algorithm for planogram compliance control by finding the optimal global alignment between two sequences by maximizing a similarity score and then evaluating how well they align overall to produce planogram alignments. Laitala and Ruotsalainen's (2023) research built an end-to-end pipeline in which DL based product detection and classification were compared to the reference planogram to compute a normalized planogram compliance error. Finally, Muthugnanambika et al. (2018) proposed an algorithm using image processing and machine learning to find and detect changes in the arrangement of objects in retail stores. Their research indicated that the proposed algorithm was capable of counting objects of similar types and helping to track changes, which could be used to detect changes occurring in planogram compliance.

Deep Learning is a recent technological advancement with significant promise for retail management and planogram compliance. However, other technological advancements, including generative artificial intelligence (GAI), have emerged as an important force in driving the next

level of AI adoption (Kshetri et al., 2023). GAI combines machine learning, image processing and computer vision (Banh et al., 2023) and uses algorithms to generate new text and images to enhance product visualizations (Susarla et al., 2023), thereby providing an opportunity to further improve planogram compliance. This creative capacity enables automated generation of shelf layouts that reflect diverse retail constraints and dynamic merchandising strategies (Nahid-Ull-Islam, M. et al., 2025). Pagidoju and Agarwal (2025) used diffusion models to generate store-specific planogram within a cloud-native architecture automatically. Their study showed a significant reduction in planogram creation time, resulting in measurable gains and demonstrable outcomes (Venkatesh and Davis, 2000), and demonstrated that GAI can be extended to constrained physical spaces with real-world limitations. With GAI, there is less reliance on real-world data because it can generate synthetic data, which is essential for planogram compliance. Synthetic data are artificial data generated by a model trained to learn the crucial characteristics of a real-world data set (D'Amico et al., 2023). Synthetic data are new datasets that mimic the original data, but are artificially generated. In terms of detection and classification, He et al. (2023) presented the first study on the state-of-the-art text-to-image generation models. They showed that synthetic data can improve classification, is suitable and adequate for model pre-training and can work collaboratively with real data. In addition, GAI can generate synthetic shelf images that capture diverse lighting conditions, packaging angles and occlusion patterns, which improves model training and reduces cold-start issues, aligning with output quality that provides perceived usefulness (Venkatesh and Bala, 2008). Wei et al. (2022) conducted a breakthrough study that proposed a multi-angle generative adversarial networks (MAGAN) that generated realistic training images at different angles for data augmentation. The research sought to create training images of grocery products from multiple angles to improve recognition accuracy. The research demonstrated that the data augmentation based classifier was able to recognize grocery products as accurately as when using authentic images. This research indicated that GAN-generated synthetic data can effectively fill data gaps, reduce the cost of manual image collection to augment limited real-world retail datasets, enhance model generalization and improve product level performance. Travucco et al. (2023) investigated whether pre-trained text-to-image diffusion models can serve as powerful generative data augmentation engines for vision tasks. They applied prompt-guided, label-preserving image edits and showed that augmented models trained on small or imbalanced datasets can achieve higher classification accuracy and demonstrability than those trained with standard augmentations.

In summary, while DL has helped to advance planogram compliance, there continue to be shortcomings with these models because they require a significant amount of data with well-defined rules and needs retraining often. Using AI for retail product detection, an essential component of planogram compliance, has been an issue due to limited training and test data (Laitala and Ruotsalainen 2023). However, GAI can address these gaps by creating models with synthetic data that mimic the real-world distribution of products, shelves and planogram configurations that adhere to the basic rules but go beyond existing data sets. While the use of AI is currently limited at retail, there is a growing rate of adoption with GAI, which is promising for planogram compliance.

Application of Technology Acceptance Model

Now that we have evaluated the potential impact of AI technologies on the effectiveness of planogram compliance, it is important to view these advancements through the lens of the TAM,

which will help to provide insight into the likelihood of AI adoption for planogram compliance. This theory provides a framework to evaluate the likelihood of adoption via two important factors, PU and PEOU. This study will also utilize a portion of the TAM extension, TAM2. The TAM2 extension seeks to further explore the underpinnings of PU in TAM. Venkatesh and Davis (2000) posit that since PU is a fundamental driver of usage intentions, it is important to understand the determinants of its construct. These clarifying constructs include both social influence processes and cognitive instrumental processes. Given the focus of this evaluation, this discussion will focus on the more relevant cognitive instrumental processes that include job relevance, output quality and demonstrable results. These cognitive processing factors are highly relevant, as thus, can help to contribute to the understanding of the likelihood of retailers adopting AI technologies for planogram compliance.

Technology Acceptance Model

As noted earlier, Davis (1989) argues that a person's perceptions impact their intention to adopt a new technology. Specifically, this theory posits that PU and PEOU are key factors in determining intentions, which lead to adoption. With regard to planogram compliance, AI has the potential to not only be useful, but also easy to use. As previously discussed, deep learning's capabilities can help to significantly improve compliance specification, detection and classification and image detection. That is because it can capture an image, evaluate the data in the visualization, analyze the data and make recommendations within seconds with good training data, which can help to improve overall shelf management and sales. GAI that utilizes training data to create new synthetic data, fill gaps in real-world datasets (Eastwood, 2023) and replace obsolete or otherwise unusable historical data (Klubnikin, 2023) is a powerful tool. This synthetic data mimics real-world patterns, which can be extremely useful at retail due to its dynamic nature and constant rotation of products. This is an important characteristic for planogram compliance, as these models can learn from current data on product variations, sizing, pricing, etc. and create new data without needing new training data to assess compliance. GAI can also generate multiple design options based on predefined objectives, such as maximizing sales or improving customer navigation that will get better options by using adaptive and continuous learning to adjust based on feedback and new data. This capability allows the models to improve performance and generate outputs that align better with user preferences and objectives (Singh, 2022). Additionally, Leibowitz (2023) contends that the power of GAI will allow retailers to conduct virtual experiments with different configurations without physically rearranging the store shelves. With successful implementation of AI into planogram compliance, retail management can make better decisions more quickly than before, as deep learning can help to gather retail data, process it and make recommendations much more quickly than in the past. This effectively can lead to improved planogram compliance, which is highly useful to retail management. Through the lens of TAM, this discussion supports the likelihood of retailers adopting AI advancements for improved planogram compliance. Not only are the recent advancement in AI useful, but they will also make the job of planogram compliance much easier.

Technology Acceptance Model Extension

Job relevancy refers to whether or not the new technology is relevant to the job, which further explores perceptions regarding usefulness. With regard to relevancy, incorporating AI into improving planogram compliance is highly relevant for retailers. As noted earlier, visualizing

products on the shelf is one of the most critical aspects of planogram compliance. As such, the recent advancements in deep learning based computer vision are highly relevant to improving how shelf data is gathered and analyzed. According to Swagler (2023), predictive AI and deep learning can help to optimize planograms and compliance by analyzing historical sales data, customer flows, shelf layouts and other data sources efficiently. While there will still be a need for personnel to take pictures for current visualizations of the shelves, they would not have to input any data or assess the accuracy of the planogram, as AI models would be able to automate that portion of the process, which can also reduce the error rate associated with a manual process. These advancements can help to improve planogram compliance, reduce errors and lower labor costs.

Output quality refers to how well AI would be able assist in performing the necessary tasks in planogram compliance. With regard to output quality, AI has the ability to significantly improve the ability of retailers to visualize what is on the shelf and whether or not the products on the shelf are in compliance with the planogram. As noted earlier, visualizing products on the shelf is one of the challenges associated with the current state of planogram compliance. That is because the current computer visioning technologies lack the ability to clearly differentiate between the products on the shelf due to package nuances in product packaging like sizes and package similarities. The advancements in computer vision and object detection, the process to visualize products on the shelf will be vastly improved and have a pretty significant increase in quality. With these advancements, the new technology will be able to more accurately visualize store shelves, differentiate between products and perform an assessment in real time.

For result demonstrability, this would be associated with the ability to link the improvements in planogram compliance back to AI tools. Venkatesh and Davis (2000) posit that new systems can fail to garner acceptance if the user has difficulty attributing the gains back to the new system. With regard to AI, retailers should have very little trouble attributing the gains of improved planogram compliance back to incorporating AI into the process. Czerniachowska et al. (2021) contend that some potential benefits of compliance include improved shelf space management, supply chain, inventory management and product assortment selection. In addition, retailers are likely to see decreases in labor costs, increased sales at retail and improved sell-through on promotions. With these benefits being realized, retail management will be able to see these gains with improved planogram compliance and attribute these improvements back to incorporating AI into the process.

Ethical Considerations

There are some impressive AI advancements on the horizon that can positively impact planogram compliance. That being said, there are some ethical considerations that should also be part of the discussion. While the list is not all encompassing, some of the key areas of ethical concern include bias, human interactions and data transparency.

Data Bias

As with most data, it is important to effectively manage it to eliminate as much bias in the data as possible. According to Feldman and Peake (2021), bias in AI systems occurs from unbalanced training data and model design choices. Correctly classifying items on shelves via DL across brands and packaging can be challenging due to the nuances on packaging (Melk et al., 2023).

There is also the possibility of demographic bias. To mitigate the potential impact of bias in the data, a bias audit should be performed when incorporating AI tools into planogram compliance. A bias audit is when an assessment of an AI algorithm's decision-making processes is conducted to identify and mitigate unfairness or discrimination against specific groups based on sensitive attributes, such as race, gender, or age (Sandvig et al., 2016). To make potential discriminatory effects observable, Raji et al. (2020) call for internal, end-to-end algorithmic auditing tied to the organization's own AI lifecycle, a concept also explored by Feldman and Peake (2021). They introduced an end-to-end bias mitigation approach that combines preprocessing, in-processing and post-processing algorithms. This approach helps to find out whether the framework outperforms the baselines with respect to several fairness metrics without significantly compromising accuracy.

Human Interaction

While incorporating AI into planogram compliance can help to reduce time and costs associated with the process, there will still be a need for human interaction. Recent deep-learning shelf-monitoring systems, such as those that redesign shelf monitoring systems to utilize deep learning, do so in a way that still anticipates human operators acting on the alerts raised by the system (Pietrini et al., 2024). Liu et al. (2015) note that store managers and in-store staff are the ones who actually apply planograms to shelves and verify them on-site, often by visually checking that the shelf matches the layout sent from headquarters. That manual, store-level responsibility persists even when computer vision is introduced, because vision models still struggle with packaging changes, occlusions, mixed facings and store-specific substitutions. As a result, there are still some concerns with ensuring data quality.

Data Transparency

Like other data sets, it is important to establish and maintain data transparency. This is especially important as AI tools become more prevalent and standardized in the industry. This can help to ensure that the proper protocols are in place to access, handle and store data are in place. One of the tactics to assist with data transparency is dataset documentation. Dataset documentation acts as a safeguard for planogram compliance, as it establishes transparency regarding how shelf imagery is produced and used across the compliance framework. Pezoulas et al. (2024) argue that thorough documentation of open-source resources should accompany synthetic-data work and that future work must address fidelity and bias in synthetic data, which is only possible if the generation process is transparent. Pietrini et al. (2024) adds to this debate by encouraging labeled datasets for shelf monitoring when using a mobile device to capture images and annotated at the product level, which will allow the dataset to be reused for planogram-compliance experiments.

AI driven planogram compliance must be designed as a sociotechnical system that is able to deal with ethical concerns. While AI can help to improve the planogram compliance process, the concerns regarding data bias, human interaction and data transparency Bias audits make model behavior visible, human-in-the-loop steps keep store-level judgment in the process and rigorous dataset documentation provides the traceability to fix performance gaps across brands and stores, allowing retailers to improve accuracy without sacrificing fairness, transparency, or operational trust. These safeguards also enhance job relevance and output quality by demonstrating that AI decisions accurately reflect shelf conditions across locations and are documented adequately.

IMPLICATIONS

Planograms are an essential part of driving retail sales and necessary for keeping up with the highly competitive modern retail market (Laitala and Ruotsalainen, 2023). However, as discussed, to achieve the benefits of having a planogram, the store shelves need to be in compliance with the planogram. This helps to ensure that retail stores are accurately executing planograms at retail. While there is no predictable timeline for the majority of retailers adopting AI for planogram compliance, there is a strong likelihood that AI will be adopted by many retailers within the near future. The following provides insight into the implications of this shift on planogram compliance, retail management and customers.

Overall, the shift to incorporating AI into planogram compliance has a positive outlook. By incorporating AI that can help to significantly improve computer vision and detection, retailers will likely see better adherence to the planograms. Additionally, the process to determine planogram compliance will likely be more effective, as AI tools have the capability to complete an assessment of the retail shelves, with more accuracy and in a timelier manner, which in turn can decrease the errors and help to increase effectiveness. Not only that, but AI driven tools can help to adjust to market changes and dynamics faster, as the data will be more accurate and processed more quickly. While there remain some challenges with DL tools as they require a significant amount of data with well-defined rules and needs retraining often, advancements in GAI are happening rapidly and expect that these challenges will be minimized in the near future.

For retail management, incorporating AI into planogram compliance can result in several benefits, including reduced costs, better inventory management and increased sales. Data will also be received faster and have fewer errors, which will help management to make better decisions more quickly. Additionally, there are management implications on two organizational levels, including store level and corporate management. For store level management, incorporating AI into planogram compliance will help to reduce labor costs, gather data more quickly and efficiently, gain flexibility in performing store audits and get better data regarding inventory. In addition, they will be able to better focus on meeting merchandise requirements, promotional objectives and sales objectives. At the corporate level, decision-makers will benefit from having better access to planogram compliance data in a timelier manner. In addition, corporate managers will be able to better differentiate between local and regional dynamics, which can lead to having products and services that better meet local and regional customer needs. All of these benefits can lead to significant reduction in operating expenses, which can help to improve profitability.

When retail stores comply with a well-designed planogram, it can positively impact consumers as well. While retailer benefits are more closely linked to the lower labor costs, increased sales and better inventory management, there is also a positive impact for consumers, including a better shopping experience and ease of finding products. To improve the customer shopping experience, many retailers use planograms to help provide impactful visual merchandising that include elements like product displays, tailored shelf placement and well displayed pricing. Mondol et al. (2021) concluded that customers are more likely to shop and purchase at retailers where the store is well-organized, there is a pleasant atmosphere, and they can quickly locate the items they desire. In some cases, consumers are deterred by stores that are not in compliance with a planogram or are unorganized. Iberahim et al. (2019) suggest that effective visual merchandising can help to establish and maintain a positive store image in the customer's mind, which makes them more

comfortable and willing to purchase. When customers are comfortable with the store layout, can easily locate products and are engaged by displays, then they are more likely to purchase.

CONCLUSION

Effective planograms can help retailers make better decisions, better understand product trends and respond to customer needs. The realities of the retail environment can make it challenging to ensure that retail stores are complying with planogram requirements. Currently, much of planogram compliance is driven by poor technology and reliance upon human interactions, which can be time consuming, labor-intensive and increase labor costs. While some of the process is utilized technology, there is a lack of an industry wide automated standardized approach to planogram compliance. Challenges with relying upon a traditional labor driven process and not being able to reliably visualize whether store shelves are in compliance in a timely manner can lead to lost sales, out-of-stocks, and increased expenses. While there remain some ethical considerations, AI is positioned to address many of these challenges. When evaluating the likelihood of retailers adopting AI for planogram compliance through the lens of TAM and TAM2 cognitive constructs, it is likely that there will be widespread adoption of AI into planogram compliance appears That being said, the For retail operations and the likelihood of adopting AI for planogram compliance, looking at the through the lens of TAM and the cognitive internal processing elements of TAM2 suggests that there is likely to be widespread adoption of AI for planogram compliance. Using a literature review to assess these factors suggests that AI adoption is likely, as AI advancements are likely to provide improved visual output, lessen data errors and provide more timely results, which fit nicely with job relevance, output quality and results demonstrability. This can result in significant benefits, including improved compliance, lower labor costs, improved inventory management and higher customer satisfaction.

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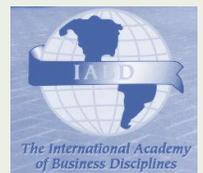
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