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PROMISES AND PERILS FOR PLANOGRAM COMPLIANCE IN A WORLD WITH GENERATIVE ARTIFICIAL INTELLIGENCE

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Abstract

In retail, planograms can have a significant impact on a customer's experience and a company's bottom line. Effective planograms can help retailers improve decision making, better understand product trends, and respond to customer needs. Given the dynamics of the retail environment, one of the major issues with planograms is compliance. Without planogram compliance, maximizing the benefits from its use may be difficult to achieve. Often, the retail environment is dynamic, filled with market nuances, rapid product rotation, and unforeseen challenges. 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 and out-of-stocks. Although some retailers use limited technology in the process, there continues to be room for improvement. Recently, there have been technical advancements, like generative artificial intelligence, that can revolutionize this process and help to significantly improve planogram compliance. This paper seeks to provide a thoughtful perspective on the effectiveness of planograms, the benefits of planogram compliance, and the potential impact that generative artificial intelligence can have on compliance.

Keywords

Planograms, Planogram Compliance, and Generative Artificial Intelligence

In retail, planograms can have a significant impact on a customer's experience and a company's bottom line. Effective planograms can help retailers make better decisions, better understand product trends, and respond to customer needs. Given the dynamics of the 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. Often, the retail environment is dynamic, 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-stock, and increasing expenses (Sadayappan and Kumar 2021). As a result, there is general agreement that incorporating technology and automation can help to improve compliance and lead to a process that is more effective and efficient than a human driven manual process. While companies use hand-held computers, cameras, and the internet for communication, the process continues to be labor intensive and prone to error. Recently, there have been significant technological advancements in artificial intelligence that can help to revolutionize and improve planograms and store level compliance. This paper seeks to provide a thoughtful perspective on the effectiveness of planograms, the benefits of planogram compliance, and the potential impact that generative artificial intelligence (GAI) can have on compliance.

Planograms

In the retail environment, there can be significant variations among stores within the same chain. This variation can also make it challenging to manage inventory, forecast product needs, and provide consistent visual merchandising. However, planograms can help to manage this variation by ensuring that the right products are being sold, the 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) supports the notion that strategically optimized planograms are instrumental in enhancing sales and overall profitability. With effective planogramming, retailers can help to drive sales and improve customer satisfaction, as such, the following provides an overview of planograms and the importance of using them in retail.

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 SKU facings should be present for each product (Czerniachowska and Hernes 2021; Goel and Sharma 2020; Laitala and Ruotsalainen 2023; Luca et al. 2021; Saqlain et al. 2022). Luca 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, Luca et al. (2021) reminds us that visual merchandising is the presentation of products in the best possible way and helps retailers to gain consumers' attention, which is a key aspect to increasing store traffic and 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). With so much store level variation and complexity, planogramming can sometimes be viewed as the art and science of designing store layouts to maximize product visibility and sales (Nexgen 2023).

Planograms are primarily used in the retail industry to help manage the products on the shelves in a retail store. That is because the major chain big box, department, grocery, and drug retailers can have thousands of stores across the United States (US), which makes planogram compliance even more challenging. 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. Please see Table 1 for details.

Table #1 2023 Top 10 US Retailers

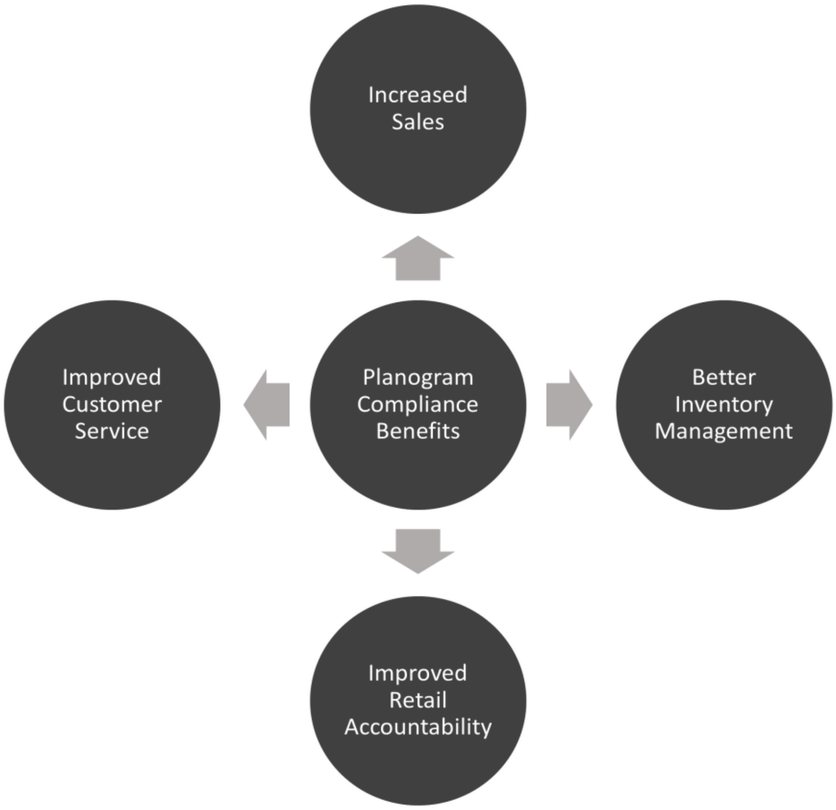
Name	Number of Retail Outlets	US Sales (billions)
1. CVS Health Corporation	9,728	$106.18
2. Walgreens Boots Alliance	8,785	$103.91
3. Walmart	5,330	$499.65
4. The Kroger Company	2,856	$147.62
5. Albertsons Companies	2,270	$76.15
6. The Home Depot	1,994	$145.94
7. Target	1,948	$107.59
8. Lowe’s Companies	1,738	$89.28
9. Costco Wholesale	574	$164.15
10. Amazon	558	$232.46
Totals	35,781	$1,672.93

Given the sheer number of store fronts among top US retailers, the importance of effectively managing them cannot be understated if these companies expect to maximize sales. Chong et al. (2016) notes the importance of compliance 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. Saqlain et al. (2022) agrees and contends 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.

Benefits of Planogram Compliance

To achieve the potential benefits associated with planograms, there needs to be compliance. Laitala and Ruotsalainen (2023) suggest that planogram compliance can help to increase sales up to 8% and that suboptimal merchandising can lead to a loss of up to 1% of sales. It is not only important to develop a planogram, but every effort needs to be made to ensure that the planogram is implemented correctly at retail so the benefits can be realized. While there are several benefits linked to planograms, this discussion will focus on the importance and benefits associated with compliance. This is an important aspect of retail management, as complying with a well-developed planogram can help to increase sales, improve customer satisfaction, better manage inventory, and improve accountability at retail.

Figure #1
Planogram Compliance Benefits



Increased Sales
As noted earlier, planograms can help to optimize the retail store environment by optimizing shelf space and standardizing merchandising. They are designed to highlight and focus on products based on trends, consumer needs, and paid promotions. One of the most critical aspects of planogram compliance is the potential impact on sales. Czerniachowska and Hernes (2021) highlight this and note that compliance can help retailers to maximize sales. A study by the National Association for Retailing Merchandising Services (Frontoni et al. 2015) supports this notion and found that a 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%. Therefore, it is important to not only focus on developing an optimized planogram, but it is also important to ensure that efforts are made to ensure that retail stores are complying with the planograms to maximize sales. With many retailers having thousands of stores, ensuring compliance is an essential, but daunting task.

Improved Customer Satisfaction
Not only can planogram compliance assist with sales, but it can also help to improve customer satisfaction. Saqlain et al. (2022) suggest that effective planograms help organize SKUs on the shelves in a way that

attracts more customers and helps them select products more efficiently. Frontoni, Mancini, and Zingaretti (2015) contend that planograms have multiple aims, including product placement, marketing decisions, and customer experience, so compliance can help increase brand loyalty and customer satisfaction. Czerniachowska and Hernes (2021) agree and posit that good shelf space allocation decisions and visual merchandising attract customer attention and influence purchase decisions.

Better Inventory Management

Another benefit of planogram compliance is inventory management, which can impact not only shelf space management, but also out-of-stocks. Frontoni, Mancini, and Zingaretti (2015) estimate that 10% of planogram errors can lead to an increase of 1% in stock-outs and decrease sell through by .5%. Furthermore, Frontoni, Mancini, and Zingaretti (2015) highlight the impact that planogram compliance can have on inventory management and note that compliance is crucial to avoid stock-outs and maintain the expected level of sell through of products. Czerniachowska and Hernes (2021) agree and contend that some potential benefits of compliance include improved shelf space management, supply chain, inventory management, and product assortment selection. Without planogram compliance, there can be a risk of mismanaging inventory, which can lead to loss of sales.

Improved Accountability

Accountability at retail is another important benefit associated with planogram compliance. Czerniachowska and Hernes (2021) note that available shelf space is a limited resource in most local retail stores so having a planogram to follow helps retail employees achieve desired sales and improve customer satisfaction. When retail stores comply with the planogram, this helps to ensure that products are in the correct place, with the correct pricing, and that all merchandising is appropriate. Goel and Sharma (2020) posit that planograms are useful for examining the point of sale, which can lead to improved store layout/design and better space utilization as it demonstrates the exact positioning of products. Additionally, the planogram helps to ensure that the store personnel are accountable for the plans and spending for the company. Without an effective and updated planogram, store level personnel cannot be expected to fulfil the merchandising requirements, sales, and revenue objectives. When the planogram is clear and current, retail employees can better understand the plans and ensure they are executed. This helps with accountability by helping to make sure products are placed on the shelves in the appropriate place, that each product has the correct number of facings on the shelf, pricing is correct, and decisions are based on trends, customer needs, and current promotions.

<u>Key Challenges with Planogram Compliance</u>

While planograms can be helpful to retailers, compliance is necessary to realize the potential benefits. Planogram compliance checks whether the products at the retail store match the desired arrangement in the planogram (Laitala and Ruotsalainen 2023). Planogram compliance is critical in achieving the expected benefits of using planograms. Saqlain et al. (2022) notes that in retail management, the continuous monitoring of shelves to keep track of the availability of the products and following a proper layout are the two critical factors that can improve sales and customer satisfaction. However, compliance is more complicated than it may seem on the surface. That is primarily due to the store level variability, constant product rotations, and the labor-intensive process associated with checking for compliance, which can make the process less desirable and prone to human errors. While planograms can be useful, compliance is a challenging but essential part of the process to achieve the expected benefits.

Using Outdated Methods

One of the main challenges with planogram compliance is that some retailers continue to use manual outdated methods, which tend to be labor-intensive and have a greater likelihood of 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. Furthermore, 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 due to the labor-intensive process. Laitala and Ruotsalainen (2023) agree and posit that the possibility of human error is always present with people conducting the compliance process. 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 planogram compliance, including out-of-stock, shelf management, and customer support. Many scholars agree that planogram compliance needs to move away from the traditional manual process and begin to incorporate more technology and automation. Saqlain et al. (2022) argue that automation is necessary for effective planogram compliance and optimized retail management. Furthermore, Saqlain et al. (2022) posited that for optimized retail management, compliance and shelf monitoring should be performed in an automated way.

Faulty Automation

While automation is available, much of it continues to be faulty 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 SKUs, assessing whether there are missing SKUs, 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. In addition to improved object detection, a more efficient automated process may include robots that help to minimize the need for human intervention. While there continue to be some challenges with planogram compliance, it is essential to continue to perform the necessary tasks, as compliance can have real benefits. As such, retailers need to ensure that there is an effective compliance process in place in order to realize the full benefits of having planograms.

This discussion provided an overview of the benefits associated with planogram compliance. This included increased sales, improved customer service, better inventory management, and improved retail accountability. However, due to the lack of technology and automation many retailers continue to be challenged with effective compliance and are not fully realizing the benefits of having planograms. As noted above, automation can improve planogram compliance, reduce labor needs, and drive down costs. 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 artificial intelligence (AI). Up next, the focus will shift to AI, deep learning (DL), and the impact these recent technological advancements can have on planogram compliance.

Artificial Intelligence, Deep Learning and Planogram Compliance

Planogram compliance is an important aspect of driving sales, improving store level accountability, and improving customer satisfaction in the retail environment. However, the traditional approach to compliance lacks impactful automation, is labor intensive, and prone to mistakes. Retail and consumer product companies have begun to realize that the traditional approach of performing planogram product detections has its limitations and needs to be reimagined in a rapidly evolving and highly competitive market (Sadayappan and Kumar 2021). In addition, there can be a lot of SKU turnover in the retail environment. This adds complexity to planogram compliance, as there is a constant rotation of old SKUs being replaced with new ones coming into the market. There has been a lot of work done to automate planogram compliance with visualization software that can automatically detect products and assess compliance. But these technologies are not fully effective, as there are a lot of similarities in product packaging that makes automated product detection more challenging, so many retailers continue to rely on the traditional labor intensive and error prone approach. While planogram compliance has been and continues to be a mostly a manual process, AI and DL have started playing a critical role in planogram assortment by helping to rank and recommend the best products to maximize sales (Sadayappan and Kumar 2021). This discussion focuses on how AI and DL can have a significant impact on the retail sector and planogram compliance.

Artificial Intelligence

Integrating AI into planogram compliance can help to revolutionize how stores manage space and inventory, ensuring optimal product placement for maximum appeal and efficiency. In the contemporary landscape of technological advancements, AI is at the center of the transformative change currently taking place in the retail sector because of its potential to fundamentally alter how retailers operate. That is because AI can analyze vast amounts of data, which allows businesses to understand consumer behavior on a granular level (Mitchell 2023). AI's role in analyzing shopping patterns aids in optimizing product placement and inventory management. Retailers have increasingly focused on utilizing AI to reshape the customer's retail shopping experience by gathering information about where products are physically located within a store and suggesting what other products might work well with the purchased item (Grewal, Roggeveen, and Nordfält 2017). AI can significantly impact the retail sector by improving planogram compliance and shelf monitoring.

Furthering this discourse, Sadayappan and Kumar (2021) underscored the transformative application of using AI and machine learning (ML) to refine retail planograms, as it can help to better rank and recommend products, gain data-driven insights, improve customer satisfaction, and enhance sales. Complementing this perspective, Muthugnanambika et al. (2018) introduced a novel automated vision-based system employing image processing coupled with ML techniques. This system was designed to identify and analyze variations in object arrangements relative to a standard planogram. Their research indicated that this method was effective in detecting several types of deviations, including misplacement, absence of expected items, and alterations in product quantities. Recent advancements, especially in convolutional neural networks (CNNs), have helped to enhance image-based compliance and product detection, which can help to overcome challenges with differentiating between products with similar packaging and sizing. Higa and Iwamoto (2019) 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. The results of one of the three experiments achieved a success rate of 89.6% for product availability, which was much higher than traditional methods.

Deep Learning

Deep learning, a subset of AI, has also been instrumental in retail. The DL concept appeared for the first time in 2006 as a new field of ML research related to pattern recognition (Hinton et al. 2006) and has an objective to learn deep representation, i.e., to learn multilevel representation and abstraction from information (Zhang et al. 2019). Deep learning emerged efficiently by showing improved performance as it can automatically process and learn the features from images, like those used in computer visualization, natural language processing, and planogram compliance (Saqlain et al. 2022). Through DL, AI can help to improve in-store shelf visualization, analyze shopping patterns, and better understand customer preferences, enabling retailers to tailor their planograms to meet consumer demands and trends more effectively. The most frequently used technique in DL is CNN, and it has outperformed traditional methods based on hand-crafted features that could not extract deep information from images (Saqlain et al. 2022). A CNN is a DL algorithm that can take in an input image, assign importance to various aspects/objects in the image, and then differentiate them from each other (Saha 2018). CNNs have shown remarkable performance on image classification tasks, which has led to more accurate results (Goel and Sharma 2020).

There have been several studies on computer visualization and planogram compliance. In their study, Chong, Bustan, and Wee (2016) employed DL to assess planogram compliance within retail establishments. The finding suggested that the CNN models exhibited superior accuracy compared to alternative models, demonstrating enhanced generalization capabilities. Laitalia and Ruotsalainen (2023) employed DL and computer visualization to automate shelf monitoring and planogram compliance. Their work focused on recent advancements in retail product detection using DL that emphasized the crucial role of product classification and localization in image-based compliance checks. Saqlain et al. (2022) proposed a hybrid approach that leverages DL's feature extraction capabilities (O'Mahony et al. 2019; Wei et al. 2020) to achieve planogram compliance and shelf monitoring. This method surpasses simple neural networks by capturing intricate product details, leading to enhanced retail management through improved layout adherence and product visibility.

Recently, DL has enjoyed a thriving expansion with enormous achievements in image classification and object detection (Wei et al. 2020). According to Wei et al. (2020), the success of DL in computer vision is due to CNNs, which stand out for their superior performance in various tasks. As DL evolves, its potential to reshape the retail landscape is undeniable, promising operational efficiency gains and a shift toward customer-centric merchandising (Saqlain et al. 2022). That said, there are some limitations with DL. Next, the discussion will shift to these limitations and the implications for planogram compliance.

Limitations with Deep Learning

In the contemporary milieu of retail marketing, incorporating AI and DL into planogram software marks a noteworthy technological advancement. This observation is supported by several authors in the field. Nonetheless, it is imperative to acknowledge and mitigate the risks and threats associated with this technological progression to ensure AI is utilized responsibly and effectively in retail environments. AI applications often raise ethical questions, including data privacy, informed consent, and bias. A notable concern is the potential for bias and discrimination in AI-generated outputs.

Given that these models are trained on extensive datasets, there is a risk that they may inadvertently perpetuate and amplify societal disparities (Wei et al. 2020). This phenomenon could result in deleterious effects for both brands and consumers. Specifically, there is a danger that AI-driven planogram generation might lead to unfair or prejudiced outcomes, such as the preferential treatment of specific products or brands based on irrelevant criteria such as race, gender (Feldman and Peake 2021), or discriminatory behavior (Mehrabi et al. 2020). These limitations sometimes overshadow the benefits of retail product detection and planogram compliance, mainly when the technology is applied without adequate oversight.

Another DL issue is the required data for retail product detection. DL models require a substantial amount of labeled training data to perform well. These models also require significant computational resources, including powerful graphic processing units (GPUs) and substantial amounts of memory (Wei et al. 2020). This can be costly and time-consuming because retail product detection and planogram compliance rely heavily on large, labeled image datasets. In addition, DL models can only make predictions based on the data they have been trained in. The models may need help generalizing to new situations or contexts not represented in the training data. Existing product designs often evolve, necessitating a flexible recognition system that can adapt with little or no retraining upon introducing a new product or package. However, CNNs typically face a challenge known as "catastrophic forgetting," where they struggle to remember previously learned objects when trained for new tasks. Leading image classification and object detection models require complete retraining to incorporate new categories (Wei et al. 2020). This inflexibility is especially problematic in retail product detection, where a rapidly changing product range leads to models needing longer retraining periods (Laitala and Ruotsalainen 2023).

An additional disadvantage of DL is that the internal logic to achieve the desired output is not explained. This behavior is called "Black Box" (Buhrmester, Münch, and Arens 2021), where there is a lack transparency or interpretability of how data are transformed to model outputs. The complexity of the black box prevents individuals from correctly understanding and auditing them, even if they produce accurate results. It can misidentify products in retail product detection without providing an apparent reason. This lack of transparency can be problematic in understanding and trusting the output from these models.

In summary, DL has emerged as a powerful tool for planogram compliance and retail product detection, offering numerous advantages in efficiency and accuracy. However, there are some challenges. These can include high resource demands, adaptability issues, and lack of transparency in decision-making processes (i.e. Black Box). In addition, there can be limitations to DL because it requires a large amount of annotated data for training and flexibility issues, CNNs because there may be a lack of recognition of some previously learned products when adapted to new shelf items, and ethical issues like bias and discrimination with some algorithms.

The Future of Planogram Compliance with Generative Artificial Intelligence

Artificial intelligence and DL are recent technological advancements that have a lot of promise for retail management, planogram development, and planogram compliance. As should be expected, there are more technological advancements on the horizon for retail management. Specifically, this includes GAI, which has emerged as a major force in driving the adoption of AI (Dwivedi et al. 2023; Kshetri et al. 2023). The commercial impact of GAI is equally noteworthy. In 2022, the GAI market was valued at $10.79 billion and is projected to have exponential growth to $118.06 billion by 2032 (Bandi et al. 2023). Korthikanti et al. (2023) posit that GAI has the potential to revolutionize many functions in business and leaders should view it as a general-purpose technology akin to electricity, the steam engine, and the internet. While GAI's influence may not be evident in today's landscape, the impact of GAI on performance and competition throughout the economy will be apparent in just a few years (Korthikanti et al. 2023).

Generative AI has emerged as a prominent field of study and holds immense potential to transform industries. The power of GAI is that it goes beyond AI models that just process data. Generative AI can process data and create new content/data. Most AI models focus on processing, analyzing, and interpreting data (Lawton 2023) and are suitable for making predictions on structured data, like the tabular data in a spreadsheet (Zewe 2023). According to Marr (2023), most AI models focus on performing a specific task intelligently and have systems that can not only learn from data, but also make decisions and predictions based on that data. These AI models are trained to follow specific rules and do a particular job, as they are determined by extant data's decision boundaries (e.g., classification, regression, or clustering) (Tomczak 2022; Weisz et al. 2023). However, these models do not create something new. This can be slightly problematic when it comes to retail product classification and planogram compliance, as there are varying rules, a lack of consistent data, and AI does not inherently explore new possibilities beyond existing data and rules (Laitalia and Ruostalainen 2023). This is not the case for GAI, which uses DL techniques like algorithms to create new content through text, images (Susarla et al. 2023), photos and paintings (Lawton 2023), and data augmentation (Cao and Li 2015). The theoretical framework of GAI comprises ML, natural language processing, image processing, and computer vision (Banh et al. 2023). Although GAI models have been around for decades, new models relying on neural networks have paved the way for significantly higher-quality generated content (Banh et al. 2023). Generative AI's ability to create content is unparalleled, including performing virtual prototyping and simulation. It enables the creation of intricate virtual prototypes and simulations that closely mimic real-world scenarios (Ambilio 2023). These recent breakthroughs in GAI models have created new tools for creating content, from photos to paintings and coding (Lawton 2023) to enhancing product visualization, which can help to significantly impact and improve planogram compliance. This recent phenomenon is rapidly disrupting retail and reshaping customer experiences, marketing, and operations (Elbayadi 2023).

One of the critical differences between AI and GAI is the use of training data. With GAI, there is less reliance on real-world data because it is adept at creating synthetic data and can play an essential role in planogram compliance. Synthetic data are artificial data generated by a model trained to learn the essential characteristics of a natural source data set (D'Amico et al. 2023). Synthetic data creates new datasets that imitate real-world data, but these data are artificially generated. Generative AI can help to create synthetic data that mimics real-world patterns. The ability of GAI to create and use synthetic data offers numerous value propositions for enterprises, including its ability to fill gaps in real-world data sets and replace historical data that are obsolete or otherwise no longer useful (Klubnikin 2023). According to Eastwood (2023), a synthetic data set has the same mathematical properties as the real-world data set. It generates a second set of data that can contain general patterns and properties of the original data, numbering in billions.

AI can help to improve planogram compliance, but there continue to be shortcomings with AI models because they require well-defined rules and consistent data. Using AI for retail product detection, an essential component of planogram compliance, has been an issue due to the small amount of available training data and test data (Laitalia and Ruostalainen 2023). Another shortcoming in planogram compliance has been dim lighting and backgrounds, making it more difficult for people to accurately check and maintain planogram compliance (Saqlain et al. 2022). However, GAI can address these gaps by creating models with synthetic data that mimic real-world distribution of products, shelves, and planogram configurations that adhere to the basic rules but go beyond existing examples. Synthetic data can artificially vary existing product images, simulating different lighting conditions, poses, or backgrounds, and is typically more cost-effective and faster than capturing new photos.

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). As noted above, equally important is planogram compliance to ensure that retail stores are accurately executing planograms at retail. Currently, much of planogram compliance is done manually, which is time consuming, labor intensive, and increases labor costs. While some of the process is automated, there is a lack of an industry wide automated standardized approach to planogram compliance. However, the future of planogram compliance is likely to change with the recent technological advancements associated with GAI and its improved visualizations and data analysis, which can help to improve and streamline the process for capturing images on store shelves. That is because GAI can capture the image, evaluate the data in the visualization, analyze the data, and make recommendations. 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 GAI models would be able to automate that portion of the process.

According to Swagler (2023), GAI can help to optimize planograms and compliance by analyzing historical sales data, customer flows, shelf layouts, and other data sources. With this analysis, GAI can generate multiple design options based on predefined objectives, such as maximizing sales or improving customer navigation. Generative AI systems can generate multiple design 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). For example, it would adjust planograms, ensuring optimal product placement even as circumstances change. Leibowitz (2023) contends that the power of GAI will allow retailers to conduct virtual experiments with different configurations without physically rearranging the store shelves. This is powerful and can result in improved inventory management, increased product rotations on store shelves, a better understanding of the nuances associated with customer shopping behaviors, and optimized store design/layout to ensure maximum product sales.

Conclusion

Effective planograms can help retailers make better decisions, better understand product trends, and respond to customer needs. However, without planogram compliance, maximizing the benefits from its use may be difficult to achieve. The realities of the retail environment can make it challenging to ensure that retail stores are complying with planogram requirements. Challenges with relying upon a traditional labor driven process and not being able to visualize store shelves to determine the state of compliance can led to lost sales, out-of-stock, and increasing expenses. While companies have incorporated limited automation, there is a lack of an industry wide automated standardized approach in determining compliance. Recently, there have been significant technological advancements in GAI which enhance its capability to generate and use synthetic data. This ability of GAI to generate new, realistic content from training data has the potential to change the landscape in planogram compliance. The use of synthetic data offers numerous value propositions for enterprises due to its ability to replicate real-world data characteristics and offer solutions for planogram compliance. While GAI is reemerging and gaining users, the projected double-digit yearly growth suggests that these advancements will soon be on the horizon in not only planogram and planogram compliance, but also a plethora of other industries as well.

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