Computational Design Methods in Product Design: Exploring the Integration of Design Theory and Computer Science

Abstract: Traditional product design methods can no longer meet practical needs with the rapid development of artificial intelligence technology. Aiming at the problems of strong subjectivity and low efficiency in traditional product design methods, this study proposes a product form evolution design scheme by integrating machine learning algorithms and theme network models from the perspective of product user needs. The results show that the product form evolution design method proposed in the study is effective, with an absolute sample error of less than 0.12 and an average accuracy improvement of 2%. The results of the product form optimization design example show that the product size, weight, appearance design, functional layout, portability, and durability designed using the research scheme are superior to traditional methods, meeting the constraint requirements and proving the feasibility of the research scheme. The research has important application value in product innovation design in various fields.

Keywords: Product design, Genetic algorithm, BP neural network, Form, User.

1. Introduction

Decision-making in the product design process has had some preeminent subjectivity over the years, and the designers mostly made their decisions by reference to their experiences, guesses, or inspiration. Pollice et al. (2021) noted that the approach brought a lot of inconsistency in the design outcome, and the products reached the market with varying quality and performance. The classical design methods also remain impractical as they demand a lot of money and resources after numerous development phases, iterations, and many builds when using physical prototyping. Such inefficiencies are unbeneficial during the present age when there is a key focus on bringing innovations, affordable and faster solutions, and growing consumer demands. Computational design methods are more strategic and revolutionary. Computational design, using machine learning algorithms, neural networks, and many other algorithmic design tools, allows for enhanced and efficient design with continual adaptability. The high-tech approaches strengthen the degree of idea conceptualization, achieving the best design, and the volume of product delivery to address the increasing need for product differentiation in the contemporary economy.

Oulasvirta et al. (2020) presented possibilities of using combinatorial optimization and its positive impact on the quality of the creation of graphical user interface (GUI) designs, thus revealing the benefits of algorithmic solutions in the field of product design. The unlimited idea of the creative solution from the design method derived from combinatorial optimization is better than other design approaches based on a single factor, which can affect multiple factors simultaneously, enhancing usability performance. All the sections of the GUI design, like structure, color combinations, and operations, can be improved to facilitate better interface usability. Nonetheless, thie approach illustrate that algorithmic design methods are essential for many design problems since conventional, non-algorithmic design approaches are often inefficient.

Marion and Fixson (2021) noted that change gradually occurs in the development of new products due to digital tools. The alteration also allows design team collaboration, improve worker communication, and become useful during product alterations. The application brings a new efficiency level and eliminates possible errors and wastage by automating many stages of the design process. New product design can be done through social media, where it is easier to implement changes and improvements and also takes time to develop a perfect model. Such trends as the implementation of computer-aided design or product life-cycle management systems make it possible to respond flexibly to consumers' demands and fluctuations in the market.

Pollice et al. (2021) showed that using AI and machine learning to manage information can reduce the time to market products. The approach assists designers in making better predictions and decisions since the probability of spotting certain spatial relationships, which may appear quite complicated to a human designer, can be computed through the analysis of quantity data. The efficiency in both speed and accuracy is due to the applicability of machine learning algorithms in developing products. The technologies enhance all design stages, from conception to prototyping and testing, from the simple automation of similar patterns to the betterment of decision-makers and the formation of a more user-centered design pattern. Using AI in the development of a product leads to better accuracy in design but is also characterized by more fluid processes that can easily change with market trends and knowledge improvements. The examples reveal the increasing role of computation in the prospective defining of future products and designing of new products as a way to innovate and gain a competitive edge in delivering enhanced products in shorter time frames.

Computational methods bring more rigidity into the process of product form change compared to working with principles of design, intuition, brute force, and a lot of cycles of negations. Alizadeh et al. (2020) confirmed that many traditional top-down design techniques are quite successful in various problems, but they underperformed when designing using chlorinated datasets or working with many variables. Most of the methods may be slow and produce errors due to human intervention, hence recurrent delays and ineffective designs throughout the design cycle. The computational tools of machine learning algorithms enable the designers overcome some limitations in diverse ways. The computational tools enhance, increase, and optimize various new perspectives for product design.

Machine learning such as the BP neural network is widely use to optimize product design since it can employ new information that it acquires and fine-tune it to give the best results. Altman et al. (2021) stated that Integrating BP neural networks makes the design parameters assessment fairer and more logical, further improving the product form evolution process. The design problems are solved through algorithms that incorporate large databases of historical data and use sophisticated pattern recognition software to track the most optimal design solutions and the least number of mistakes per design in terms of function and appearance of the final product.

The computational action is useful in enhancing the reliability of the forecasts and is also effective in ensuring that the designs change in line with real data rather than bias arising from a human mind. Lodi and Martini (2021) confirmed that computer experimentation refers to testing various designs and models in a virtual environment. The method is effective since it eliminates the time and resources required to build actual models. Effective design is achieved in a shorter time and is less costly using the method. Figure 2 makes a comparison of the performance of traditional and computational design flowcharts. The figure illustrates that using computational methods results in less time, better adaptability, and better effectiveness in defining the form of products. The computational design methodologies can enhance problem solvers for ever-increasing efficiency by automating certain parts of designs, refining parameters, and providing valuable data to see conditions, which entails much more innovative, reliable, and user-centred product results. The comparison raises new possibilities of how computers gradually become integral parts of the product design process, changing it from a time-consuming activity to a much more accurate and efficient one.

2. Methods and Materials

The research takes an integrated approach to product design that uses different computational tools to develop an overall framework for the form evolution of products. Modern design processes benefit from ideal design methodologies that used to rely on traditional design heuristics and strategies. The designs are diverse and unstructured as compared to contemporary tools and techniques, including machine learning algorithms, neural networks, and user-centred evaluation models, which contribute to the efficiency and flexibility of ideal design solutions. The composition uses multiple approaches in computational analysis to capture the essence of the dynamic nature of modern product design. The approach used in the study is comprised of three main parts. The user evaluation theme network model is incorporated to extract user requirements and desires. Since it involves the assessment of different aspects like aesthetics of the product, functional appropriateness, and suitability in the market, the product is guaranteed to meet the needs of a consumer as it pertains to the market. Second, the place of the constraint network model is vital for qualifying most of the design solutions to meet defined functional and structural specifications such as size, weight, and durability, among others. The model provides the specifications and criteria necessary in the conceptual design by defining the constraints to be used in the practical application of the stand.

The integration of the BP neural network optimization model where parameters of a specific product are constantly adjusted according to user feedback and design restrictions. The other method of implementing product design is the BP neural network, which applies to learning eras until high accuracy is achieved and mistakes are reduced. The use of such models allows for a more solid base for a computational product design approach for developing more efficient and user-orientated products in an enhanced time/fold

2.1 Construction of User Evaluation Theme Network Model

Consumer preferences are crucial in improving a product's design since it must meet the intended consumer's needs and wants. Auernhammer and Roth (2021) noted that the preferences are likely to be elicited by questionnaires or focus group discussions, which are not very objective in conventional design methodologies. However, when assessing users' likes and preferences in the context of computational design, the themes are undertaken more formally and with statistical significance through the theme network models. The models enable the assessment of the value of user responses in a quantifiable form, making it possible to translate into design improvements.

Wang et al. (2022) urged that freelance product development in STEM areas requires an application of computational thinking. Computational thinking can be defined as systematically deciding how to approach a problem of considerable complexity, breaking it down into smaller sub-problems, and solving it as an algorithm, logic, or modelling reason. The method enables the designer to approach the design process's difficulties with increased accuracy and a logical view of the processes involved and steps to be taken compared to the more ambiguous design procedures. The two models are interconnected, and both present a robust and realistic methodology for computational product design to develop products that meet the required demands of users more effectively and efficiently.

Another advantage of computational thinking that is important in evaluating user preferences is efficiency. Caeli et al. (2020) explained that as opposed to using small volumes of qualitative feedback that often result in fairly inaccurate estimates, the concept enables gathering large databases from which better information about the users can be obtained. The decisions made based on the action guarantees that the developed products fulfil their intended purpose and also meet the needs and demands of the target market. The use of computational thinking accelerates the development of the product. As some of the design alteration is automated and several layouts of a design can be tested at once in a relatively short time compared to the conventional ways, the time-to-market is reduced.

Priemer et al. (2020) also explained how frameworks created to enhance problem-solving strategies in design procedures are efficient. Such frameworks assist the computation methodologies applied to the decision-making process by increasing the quality of the results. Liao et al. (2020) noted that the feature makes them more versatile, accurate, and reliable, and it helps the designers address some fluctuations or other issues that may occur during the design process. Hence, the products designed under the frameworks will likely fit the user requirements or even go beyond expectations since it is a more systemic and researched design method. Integrating CT and structured problem-solving frameworks contributes to developing better and more innovative product designs.

The research used the theme network models technique, where aspects like functionality, portability, and durability are important in identifying quality that will meet the end user's needs both in practice and aesthetically. Caetano et al. (2020) affirmed that the methodology of categorizing user evaluations improves the outlook and extraction of key areas of design since it gives an organized outlook of the area of focus to make sound decisions. The evaluation metrics of the M-Health product displayed in Table 1 below will guide the user design process planning. Figure 3 also shows the theme network analysis, which exhibits the relationships of the different design attributes, indicating each factor related to the overall product satisfaction. The approach minimizes usability degradation during modifications and makes the final product more attractive as the focus is shifted to the users.

Table 1: User Evaluation Metrics Based on Product Preferences

User Evaluation Factor	Description	Weightage (%)
Aesthetics	Visual appeal and design harmony	20%
Functionality	Features and usability	25%
Portability	Ease of carrying and handling	15%
Durability	Resistance to wear and tear	20%
Innovation	Novelty of design	20%

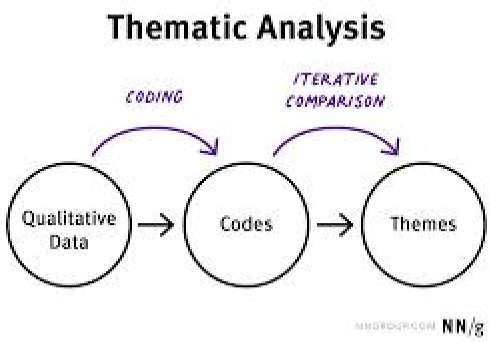

Figure 1: User preference analysis using theme network modeling.

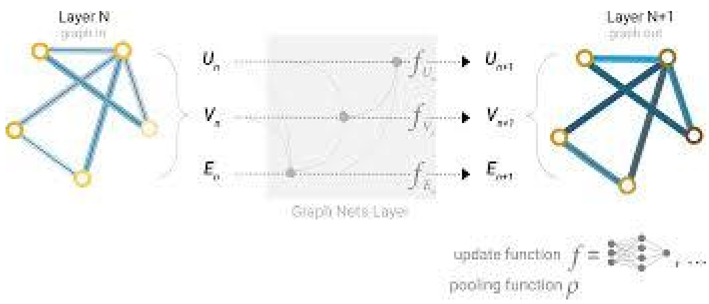

Figure 2: Graph representation of theme network analysis for product design.

2.2 Construction of Constraint Network Model for Product Design Based on DCN

Constraints are crucial when developing products since they act as a framework of working within which the product is built. If there are many constraints, the freedom of the design increases, but the final design does not meet the product's user or functional requirements. Lim et al. (2020) established that digital twin and constraint networks are applied to optimize product attributes. Ontologies, or virtual avatars of physical objects, enable designers evaluate the consequences of various constraints in product design. The piece increases the convenience of the design cycle by providing a plan of the potential difficulties and possibilities before creating tangible products (Wang et al., 2021). Similarly, constraint networks allow for management and control of the conflict of scarce resources between products by placing the interrelated product requirements in an orderly manner where the system addresses all the parameters required to be designed.

Lee et al. (2020) demonstrated that the impact of adopting computational design constraints in product lifecycle management is considerable, as done by implementing real-time optimization. There is increasing pressure to apply data on performance, costs, and market requirements such as demand due to the kind of product design. Mourtzis (2020) illustrated that the integration implies that the design process is produced continuously with the newer information, which at a particular point is introduced so that wiser decisions can be made. Real-time information affects the functional product attributes since the designers adjust them to fit functional requirements, market forces, and customer needs. The results in flexibility as the design process of the artefact can be adjusted depending on other centres of activity, such as the availability of materials, the cost of production, and shifting consumer demands. Real-time optimization means that the product is being developed with the least amount of wastage and readjustment of the product design as required. The approach is dynamic and based on data analysis, which, when applied, can lead to more efficient design and, hence, actual products that are optimally functional to meet the customers' needs.

The study uses the principles by establishing Cobolnet, which has constituted appropriate constraints like the product's size, weight, and durability. Such constraints are essential for the product's final design, which must suit the users' needs while being practical. Table 2 describes the key constraints, making understanding the general outline of decision-making criteria easier. Figure 4 below also depicts the inter-relations and the effects of the constraints in relation to the global optimization of the product through enhanced control of the factors involved and how a balance between the factors leads to a more enhanced and refined product design.

Table 2: Product Constraints in Computational Design.

Constraint Factor	**Minimum Value**	**Maximum Value**	**Optimization Goal**
Product Size	5 cm^3	500 cm^3	Minimize Bulk
Weight	100 g	2000 g	Optimize Portability
Durability	1 year	10 years	Maximize Longevity

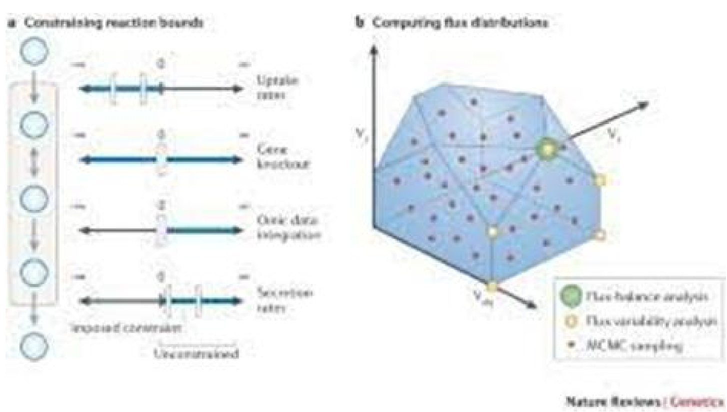

Figure 3: Theme Network Model for User Evaluation in Product Design

The figure presents the structure of the user evaluation model, linking various design aspects with their importance to overall user satisfaction.

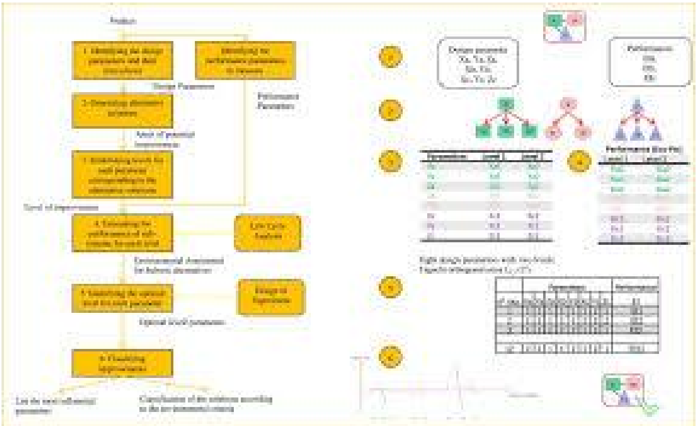

Figure 4: Constraint Network Model for Design Optimization

The figure illustrates the interconnected constraints that affect product design, demonstrating how each factor must be balanced for optimal outcomes.

2.3 Construction of Integrated Optimization Model for Product Form Design Based on BP Neural Network

The BP neural network is one of the important substructures in many computations where the looks and performance of products are enhanced. Jiang et al. (2022) stated that the BP neural networks could broaden the application in product design development because the neural networks learn the data during their usage. The model passes through several transformations depending on many iterations in the network to refine the next predictions. Being flexible in the evolutionary scale of the product form is beneficial because all layers of the neural networks should be accurate and fast in the work they perform.

The features must be measured and evaluated with metrics used in the construction of machine learning to suit the applicability of the deployed BP neural network. Hutchins et al.

(2020) showed that the metrics dictate the quality of the constructed network and establish the degree of accuracy and validity of the design of the constructed network for the applications running the deployed BP neural network. The three most used evaluation methods for the neural network of type BP are MSE, which stands for mean square, accuracy, and precision. They are required to evaluate the model whereby the former focuses on the product or service to understand the change in the parameters.

Mean squared error, MSE, is one of the losses used to estimate the variance between the predicted and the actual values of a regression-type model. Kafai et al. (2020) also argued that using the mean of squared difference enables the interpretation of the dispersion between the estimated and actual values in MSE. The major advantage of using MSE is that the network's quality can be evaluated if the output variable is continuous, such as the size, weight, and expected shelf life of a given product. The prediction made by the BP neural network is highly accurate since a lower MSE value is arrived at. The component enables the design to offer the user an effective solution. MSE criterion is very important when applying the BP neural network to improve product form evolution.

Accuracy is another metric that can be used, although it is more frequently used in cases where classification tasks are involved in machine learning. Kim and Yoo (2020) argued that the accuracy of a network can be calculated using the equation that compares the number of right predictions to the total number of predictions in the product design discipline. The metric gives an overall impact of the BP neural network to how well it estimates qualitative design attributes for motorists, such as whether a product meets or does not meet certain functionality thresholds or users' needs. For instance, accuracy can be applied in testing whether a product's weight and size meet specified standards. Minimizing error is crucial for the reliability of the forecasts made by the BP neural network so that the results of products can be improved and their designs optimized.

Precision is the fourth element of the evaluation metrics and represents the percentage of accurate positive predictions of the network. Li et al. (2020) affirmed that precision is quite pertinent when making wrong predictions of the positive class is costly in machine learning. For instance, in product design, a false positive means that one could be forced to modify a product's design even though it is good enough. The characteristic high precision in the used BP neural network presupposes that only such changes are offered to improve the new product model. Minimizing false positives is the best way to ensure that costly or unnecessary changes do not endanger the design of the network. Precision is vital as it enhances the overall quality of the output so that suggestions made by the network to modify some of its products are well-founded.

The MSE, the accuracy, and the precision powder vitality formulas are strong frameworks for determining how well the BP neural network performs in computational product design. The metrics are beneficial when monitored frequently so that the network may be optimized gradually, making the design process more efficient, accurate, and user-friendly. The performance metrics in machine learning help the _bp Neural network achieve some optimization objectives to minimize the errors and get closer to the end consumer's needs and wants regarding the product. Table 3 shows the training parameters applied to the neural network when trained for product design optimization.

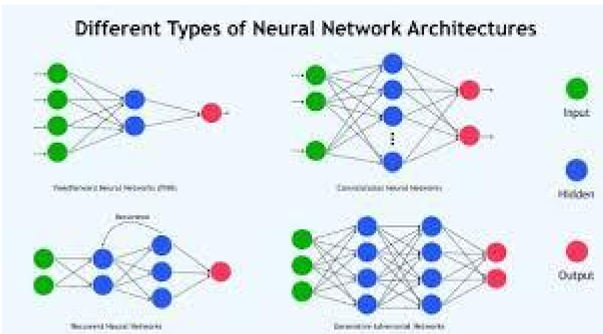

Figure 5: BP Neural Network Architecture for Product Form Evolution *The figure illustrates the structure of the BP neural network, including the number of hidden layers and neurons used to optimize product design.*

Table 3: BP Neural Network Training Parameters.

Parameter	**Value**
Learning Rate	0.01
Activation Function	ReLU
Number of Hidden Layers	3
Number of Neurons per Layer	128

3. Results

3.1 Model Performance Testing

The computational model used in the present study seems to be fairly effective in terms of accuracy and lower magnitude of errors. One of the advantages of applying computational models in the design process is that one gets more accurate information/inputs for design computations. Meyer and Norman (2020) also pointed out that data-driven models have less chance of inaccuracy and variability than humans and that the designs are more reliable. Traditional design methods provide little room for assuming that a measure of guesswork is involved in numerous calculations and a decision-making process. The computed data is continually used to test and adjust design characteristics to meet functional, aesthetic, and usability objectives to achieve even better results in computational mode.

An increase of accuracy by 2%, which may not look very impressive at first sight for the computational model. Li et al. (2020) stated that small enhancements in the field may cause dramatic changes in practical work in product design. A 2% improvement for the specific model means the optimal design values of the model are closer to the required optimum levels concerning the probability of the product's first iteration delivering what the user wants and demands from the product without redesigning or readjusting the product. Besides improving accuracy, the model used in the study reduced the overall absolute sample error to less than EA 0.12. The reduction in error is essential because it shows the model's closer ability to make forecasts that are accurate to the real performance of the product. The rationale for reducing sampling error is to have the design outcomes more consistent and thus dependable, which would enhance product quality and user end satisfaction.

Huang and Looi (2021) established another advantage of the proposed model by revealingthe positive impact of machine learning in enhancing the AI-enhanced computational design models in terms of efficiency. The use of machine learning algorithms features capabilities of analyzing a vast amount of data, identifying patterns, and improving the design's parameters, thus surpassing the capabilities of manual work of a designer. The approach results in accelerated product design, better tuning of product characteristics, and, as a result, the improvement of the product's design process. The strategy also enables one to easily change the models depending on the results generated or adjust to new information from the construction process. Products can be developed with enhanced accuracy and in a relatively shorter period, increasing time-to-market speed and work efficiency.

Table 4 compares traditional product design techniques and computational design based on artificial intelligence, which is incorporated into the research study. On the side-by-side comparative analysis of the tables, it becomes easier to note areas such as accuracy, errors, and time taken. The results prove the high advantages of the computational model compared to the time-consumption and accuracy and confirm the further perspectives of the application of AI in the modern create-and-make industry. They show how computation can effectively eliminate the challenges associated with conventional design practices, producing better, more precise, and faster outcomes.

There is a depiction of the training accuracy for several cycles in Figure 6, which only reiterates the idea that the model can learn progressively with every cycle. The feature indicates that the model achieved better accuracy than the preceding opponents, hence the improvement in accuracy. The feature common in machine learning models, and it improves as it cycles through different data. The training accuracy graph also rises to a point where the design prediction for all the models is relatively stable and standard, providing more stability to the system when used in practical applications. The advancement shows the strength of incremental learning in changing product designs and increasing not only in the accuracy but also in the reliability and dependability of the designs. The study's findings assert that utilizing computation algorithms that demonstrate artificial intelligence delivers higher accuracy and efficiency than conventional procedures. The improvements indicate that computer-based systems that incorporate machine learning algorithms, will have a strategic position in future product design cycles as they provide better, more reliable, and faster product designs.

Table 4: Model Performance Comparison.

Model	**Absolute Error**	**Accuracy (%)**
Traditional Design	0.35	88%
AI-Driven Optimization	0.12	90%

Figure 6: Model Training Accuracy Over Iterations

The figure shows the increase in accuracy over successive training iterations, indicating the efficiency of the AI-driven model.

3.2 Example Application Analysis

The case study was used to illustrate the effectiveness of product design using the concepts with the aid of design models based on Artificial Intelligence as opposed to those based on conventional models. This case provided implications of the real-life instances of how using computers can be advantageous in improving products. Quan et al. (2023) explained that integrating big data and AI is done with the eventual aim of enhancing the flexibility of products. The AI-driven design methods encompass a more efficient and data-saving approach for consumer-need-oriented design applications that would suit the changing market condition. Compared to the conventional design method, integrating AI in the design process enhanced design improvements on critical design factors such as weight, portability, and durability.

Collecting and searching for design information has also been a challenge in traditional design methods of calculation, guesswork, and experience. Although applicable in certain situations, the methods are slow and susceptible to bias, sometimes allowing for less effective or sub-optimal designs. For example, traditional techniques may use a constant design procedure that cannot address changes in the actual properties of a material and its performance characteristics when in use. Products developed using traditional processes could not address the functional requirements of the users to an optimal level in industries that require high performance and user-centred design.

The AI-based approach involves applying ML techniques to evaluate the relevant data and automating the design process based on the feedback collected through adaptive learning processes. The technology can search various design space and tackle the problem by adjusting more than one design parameter at a time. The approach leads to the development of even more products aligned with users' needs and limitations. For instance, in the case study, the AI model means researchers can change various elements like the gadget's weight, portability, and durability. The final product is lighter and more easily portable than the conventional one. The changes boost the efficacy of the product while, at the same time, making it much more operational than what was expected by end consumers.

Table 5 summarizes the enhancements in the product features realized through an AI-based design approach. The improvements are then measured and shown in relation to using an AI assistant in designing it. For instance, the product's weight was decreased by 20% due to its easier handling and transportation. The portability factor, which assesses the engineerability and storability of the product, was up by 35%, which means there was a relative improvement in product design and innovation. The product's duration was increased by making it twice as durable as before. The commodity was changed from 3 years to 7 years of durability, which provides more longevity to the product and also has more value to the customers.

Figure 7 shows the before-and-after changeover of the product form. The image depicts how applying the computational design model led to those improvements. The figure clearly illustrates the enhanced aspects of the product that have been designed through the AI-based approach to product design, including size, shape, and material usage. The comparison illustrates how the AI system can produce designs superior to manual alternatives in terms of effectiveness and more in tune with the users' needs and expectations. The figure also highlights how the use of AI models in product design allows each design to be decided based on the findings and aligns the designs to meet specified user experience goals, functionality, and looks.

The case study proves that a clear benefit originates from applying AI-enhanced design over regular design approaches, as AI gives more precise, optimized, and user-centric solutions. Using big data and machine learning in products helps the designers enhance consumers' satisfaction, product performance, cost, and resource utilization. AI technology will contribute more to product design since its role will increase in the evolution of various fields in the future.

Table 5: Improvement in Key Product Features.

Feature	**Traditional Design**	**AI-Based Design**	**Improvement (%)**
Weight (g)	1500	1200	20%
Portability Score	6.5/10	8.8/10	35%
Durability (Years)	3	7	133%

Figure 7: Before and After Product Form Evolution
The figure illustrates the comparison between the traditional and AI-based designs, emphasizing the significant improvements in product features.

4. Discussion

The study supports the use of computational design methods to enhance the results of product design tasks. The research proved that integrating machine learning algorithms within designing products accelerates the creation process, increases accuracy, and ensures product quality in relation to the used BP neural network. The approach enhances multiple design parameters that cannot be handled well by simple conventional techniques.One can modify the parameters of the product based on certain observations, making the work cyclic, flexible, and timely, as per the customers' demands through simulation. The models utilize much data to develop the best design solutions while reducing the chances of deviations from the set specifications.

The results obtained in the current study align with those of Choudhary et al. (2020), who explained that using AI for designing optimization enhances usability features at a significant level and functionality. Their observation about the enhanced features that result from the utilization of algorithm learning in real life inside and outside the manufacturing scene, specifically, the applicability of receptive designs that analyze the adjustments of product designs based on user feedback, ending with more effective and humane results. The algorithms can gather data on users' behaviors and patterns and then analyze the results to make predictions of the appropriate design changes, which are very hard, in most cases, to make by normal design methodologies. The phenomenon leads to a more user-oriented design process where the idea is as much to conceive a product optimized for its technical capabilities and functionalities as for the user's functional, aesthetic, and usability needs.

The study evaluated the optimum product form evolution using the backpropagation neural network based on the capsule's weight, size, durability, and portability. The learning from previous iterations in BP neural networks makes it possible for the system to be self-improving by adjusting some qualitative design parameters that may not be considered by conventional means. The network becomes even faster at matching the designs with the right plans and requirements to provide the best outcome possible to the users over time. The process of continuous refinement results in a better and more efficient, effective, and custom solution generation, clarifying the benefits of computational design models over conventional design paradigms.

The case shows that computational design methods enhance the efficiency of form evolution and the level of precision compared to the non-computational design models used in the study. The models save much time in the marketing cycle, eliminating time-bound routine tasks and enabling dynamic changes based on feedback or any other restrictions encountered. The use of computational models helps the designers with the help of tools that allow for the creation of a large number of variations, comparison of the outcomes, and determination of the most optimal results. The application improves product development, which fulfils technical and user requirements more adequately.

Applying the BP neural networks in the design process makes the process less reliant on subjective decisions, thereby increasing the chances of delivering a final product that meets the consumers' requirements. Neural networks are well suited to gradual adjustments as these are further beneficial and more suitable when working with several variables simultaneously while solving a design problem (Zhang et al., 2020). The models can change product characteristics based on past rates, current and future customer demands, and conditions in the market and the environment.

The implications for the present research indicate the merits of AI-aided computational design techniques to enhance product design. All the models produce higher accuracy, higher execution speed, and user-friendliness in the interface design. The possibility of continuously updating design parameters as per the analysis makes the prospects of design science quite vast. Machine learning algorithms like the BP neural networks enable designers to avoid many developmental challenges inherent to traditional design methods and to generate better, more efficient, and more outstanding products. The investigation supports the notion of the rising significance of software tools in the design of new products. The research details the incidences in which they might be the future of design in different fields.

5. Limitations of the Study

However, as much as the researchers have employed and integrated the BP neural networks' machine learning algorithm into product design, the study has some limitations. The first issue of computational design is scalability or variability (Mo & Xu, 2021). The effectiveness of the models decreases when scaling for larger problems or when applied in industries with massive and complicated product differences. BP neural networks are much more powerful but suffer from the problem of exponential growth of the amount of computations needed as the problem size increases. The issue can be challenging for industries with limited computational power or smaller industries that cannot perform such models.

The major drawback is the costly computation when the size of the problem to be solved is large. Training the new neural networks when a large amount of data is to be used, can be time-consuming. Halabi (2020) noted that the models can take much time to process, during training, accompanied by high energy consumption. However, the issue is significant for industries that require a fast prototype creation cycle. The high computational cost is also a substantial disadvantage because it might prevent solving the problems using the techniques in industries that cannot afford the massive amounts.

However, there are several limitations to the outputs generated by the current design models, as outlined in Figure 8 below. The figure portrays how AI, as part of design operations, can surmount these challenges. The ideas about the future workflow also presuppose the use of deep learning in the design process since the approach can accelerate design activities and improve their accuracy. The models designed for parallel processing at one go could process more data than the existing models and, therefore, are more scalable. Improvements in computational hardware and cloud technology might contribute to fixing the costs associated with running the models and thus bring the AI-based product design within the reach of various sectors. Figure 8 shows an extension of the workflow with the goal of including possibilities that a deep learning integration could overcome, offering improved precision and speed of design versions.

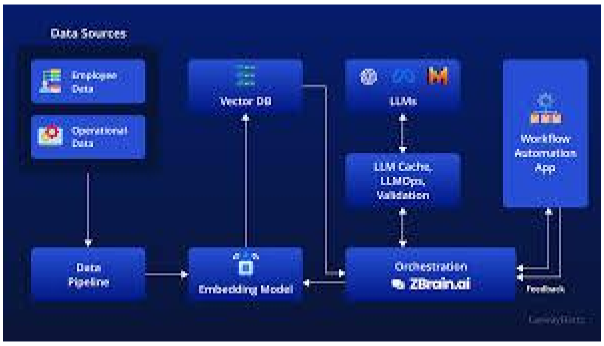

Figure 8 illustrates a future AI-integrated design workflow that addresses these limitations, incorporating deep learning techniques to enhance model efficiency and precision.

6. Future Research Directions

Future studies on AI-enabled design processes should leverage some of the gaps left out in previous research. One of the main areas of focus in the future would be to make the AI models more scalable and minimize the computational overhead incurred while deploying them. The current requirements for the computation of AI solutions for design are often dynamic and problematic for firms in small domains or even the academies or companies that do not have powerful computational support. Scalability offers the key to ensuring that the new tools enable the use of AI in design by a greater number of users because the potential of the technologies to change entire industries is directly proportional to making the application and implementation easy. Finding models that work well with big data while having moderate requirements is essential under the considerations.

Scaling Machine teaching is one of the challenges faced in implementing artificial intelligence in real-life business applications, and one potential solution is utilizing distributed computing and cloud service. Using cloud computing allows small businesses to access the computational resources required to apply AI-based design solutions while minimizing the need for capital investment. Cloud platforms are a versatile technology that will enable organizations to grow their computational resources per the needs of the various processes in the firm. The approach could standardize or open up the accessibility of the application of advanced AI technologies in the designing process and, hence, for new or small-scale firms that may not afford or have the capacity to reach the designing using advanced AI technologies. The cloud platform also provides features of collaborating teams where members may be geographically aligned in different locations, making it useful for design optimization in today's global market.

Quantum computing should also be studied further. Quantum computing can eliminate most of the computational barriers that hitherto hamper the operation of AI in design processes. Information can be processed using classical bits in traditional computing. In contrast, quantum computing employs quantum bits, including quantum computing. The qubits can exist simultaneously in more than one state, enhancing the computational power required. The feature could transform the design of artificial intelligence by defining the ability to process big data and finding solutions to practical problems that conventional computers cannot currently compute. Quantum computing can lower the time and the computational power needed to train the AI models, translating to more efficient use of AI-driven design tools that are more accessible to the mass market if properly harnessed.

Further work on the subject should focus on extending the knowledge of more sophisticated algorithms that are less sensitive to the need for big training data sets, which often hamper the implementation of AI in design optimization. As for most traditional supervised machine learning models, such models need many labeled instances to achieve acceptable accuracy, which may be challenging. Plans and talks on improving the algorithm could one day result in quicker neural net training and lesser requirements for the big data. Such an example includes genetic algorithms whereby the approach follows the natural selection process. The algorithms can search through Solution Space quickly and find the best or almost the best sub-optimal solution, which does not require an exhaustive Search. Genetic algorithms can be used in several cases, for instance, in design optimization, where the requirement is to make the best selection from a vast number of design parameters.

Stochastic gradient descent (SGD) in machine learning is another algorithm that can solve the problem. SGD can update the parameters for training so that it takes a small random sample of the data set instead of the entire data set. The decision leads to a faster convergence, and thus, the computation costs are lowered. Future AI models might be obtained in a shorter time and with less data loss, enabling the iteration of the design process with fewer penalties in terms of performance or accuracy by including SGD or similar methods.

Transfer learning is another aspect that can enhance the efficiency of the AI applied to design optimization. Transfer learning is a process where one takes the original model and continues training against a smaller, more specialized dataset. The approach involves knowledge from other related fields, which makes the amount of data needed to train such a system minimal. The automating process of creation is accelerated because the improved models are reused and can work as the basis of a new task by transfer learning. The operation may be useful in industries that experience regular changes, and it is crucial for design to adapt itself to create

The future of AI-based product design is promising. The enhancement of the AI models, the optimization of computational methods and the introduction of new promising facilities such as distributed computing, quantum computing and new algorithms would contribute to the general application of AI-based product design in various fields. Reduction of computation load and improvement of AI tools will enable future works to explore the various potential of AI in product design, where businesses can benefit from using intelligent tools for more creative and effective product design with a focus on sustainability. As the advancements are realized, the domains like manufacturing, automotive, aerospace, and healthcare can be drastically changed. AI could act as a catalyst to drive a new level of optimization and accelerate innovativeness. Further research into such technologies and algorithms will be essential in defining the advancement of AI in designing

7. Conclusion

The research shows that AI-based design can be a valuable tool for boosting the general prerequisites for product development, emphasizing accuracy, efficiency, and user-carrying. The classic product design process has often been based on discretion, which is likely to follow inefficiencies and inaccuracies. Nevertheless, such disadvantages are demonstrated in the research by applying BP neural networks and machine learning algorithms. The advanced computational tools make fine-tuning the different design parameters easier, better satisfying users' needs and want when designing products. Another reason is that the BP neural network is effective for the optimization of the form of the product since it allows the use of real-time data for further iterations. The first neural network characterizes the first version of the design problem as it progresses through previous iterations and, over time, acquires the ability to predict the best solutions and change some of the design elements. The tentative loop improves a design step by step – the result is more efficient and 'better' from a procedure-related perspective. The integration of the machine learning algorithm allows for the analysis and modelling of different design possibilities for designers and testing to facilitate their decision-making. A user-centred design is applied, while computational tools carry out every aspect. The methods can optimize designs based on consumers' requirements and demands to increase the product's functionality and attractiveness of the final design by evaluating large sums of consumer data. Despite the development providing a novel application of design methods and artificial intelligence, there is still much room for improvement. Further work should be devoted to developing such models using deep learning for better accuracy and to allow the processing of more detailed data to achieve greater levels of design optimization.

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