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Evaluating UX Design Factors Affecting Efficiency of Composite Material Design and Analysis Platforms

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Abstract

Within engineering software platforms that involve the design, simulation and characterization of composite materials, user experience (UX) design has become a key determinant for efficient use. This research aims to quantify how user experience design parameters relate to productivity in composite engineering workflows by analyzing the relationship between usability, learnability, accessibility, complexity of the UI, navigation efficiency and users engineering results satisfaction. Computational techniques in python were used in the analysis of a dataset of 400 observations that can be used for design and analysis of composite materials. Both explanatory and predictive relationships were investigated using descriptive statistics, reliability analysis, Pearson correlation analysis, multiple linear regression, mediation, machine-learning prediction models, and analysis of variance. The results suggest that the factors of usability and user satisfaction positively affect the productivity of composite engineering platforms, and that interface complexity negatively affects the productivity to a high degree. The relationship between learnability and productivity was found to have a statistically significant positive contribution, while accessibility represented a relatively minor direct contribution to productivity. This mediation analysis showed that the link between usability and engineering productivity is partially mediated by user satisfaction, demonstrating both direct and indirect benefits of good interface design. Among the various predictive models tested, the Random Forest model yielded the greatest coefficient of determination (R2 = 0.949), showing outstanding predictive power. The results highlight the significance of user-centered interface design in composite material modeling and characterization systems and reveal that UX based metrics may be used as a good proxy for engineering productivity. It offers practical advice to anyone who develops composite engineering software, works with composite materials, and is designing software or hardware to perform effectively in design processes and make sound decisions, with a focus on improving user experience.

Keywords: User experience, software development efficiency, usability, developer satisfaction, machine learning, productivity analysis

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INTRODUCTION

In the current technology-driven economy, software development has become one of the most crucial pillars of innovation, digital transformation and competitiveness of organizations. With the growing pace of digital platforms, enterprise software systems, mobile applications and intelligent computing environments, there is a greater need for efficient software development practices. In the recent years, organizations are relying on software products not only for the automation of their operations but also for decision support, customer engagement, and business growth [1–2]. Hence, the productivity in software development is a primary focus in software engineering and software management studies. In general, traditional software productivity studies have focused on technology aspects like programming languages, development platforms, software design, testing policies and project management practices [3–4]. While these factors continue to be pertinent, much has changed in the world of software engineering, and human-centric design (HCD) can also be a key factor in the success and efficiency of software development projects [5–6].

User experience (UX) design is one of the several human-centered design aspects that has come into the spotlight for its close correlation to software interaction, usability and user satisfaction [7–8]. The UX design is the experience of the user using the software system, including the usability of the user interface, learnability, flow of navigation, accessibility, clarity of information and user emotions during interaction [9–10]. In the beginning, UX research was largely about understanding how happy end-users are and how they interact with digital product. But, more and more, modern software engineering environments are aware of the fact that UX design can also have an impact on software development teams [11–12]. Throughout the software development lifecycle, developers are dealing with the interfaces, dashboards, development environments, workflows and collaborative tools on a regular basis. Thus, user experience can impact the speed at which software is developed, whether or not the tasks are completed, code quality, and software delivery efficiency [13–14].

In the real world of software development, teams typically encounter a variety of digital platforms, including project management tools, design systems, code repositories, deployment dashboards and communication systems [15–16]. If these interfaces are intuitive and easy to navigate, the developers can carry out their tasks more efficiently with less cognitive work. Conversely, the poorly designed interfaces, unnecessary complexity and hard to navigate structures can interrupt workflow continuity, enhance frustration and lower productivity [17–18]. This suggests that UX design can have a wider impact than customer-facing products, and that it is important to consider UX design as a key player in software engineering performance. While more and more organizations are becoming aware of the importance of UX in software development, many still see UX as a standalone post-development activity that is not included in productivity evaluation and project planning. This leaves a void in the studies on quantifiable impact of UX on software development productivity [19–20].

Previous studies have looked at software productivity from both technical and managerial aspects, which include agile practices, automation tools, team collaboration and software process optimization [21]. There are also some studies that have examined usability and interface design from customer experience and system acceptance point of view [22–23]. A relatively small amount of research, however, has been conducted to quantify the impact of UX design factors like usability, learnability, accessibility and interface complexity on software development productivity. Moreover, studies into the links between UX design and developer satisfaction have not yet been applied to statistical and predictive modelling [24–25]. There are also scarce empirical studies providing explanation of how UX might relate to productivity – either directly or indirectly via developer experience and satisfaction. The absence of integrated quantitative evidence provides an opportunity for systematic investigation.

In recent years, the need for advanced materials, usability concepts and user centered evaluation techniques in industrial and product design has been proved. [26] pointed out that high performance polymers and modelling techniques are emerging as more and more significant in industrial applications, contributing to the development of light, resistant and efficient products. [27] conducted another parallel study on the virtual reality design environments that study the factors having a significant impact on users' efficiency, experience, and workload when interacting with products. The design of the balance between usability and emotional product design has also been a topic of great concern, as van [28] have shown that good product design demands a delicate mix between functional performance and user satisfaction. Likewise, authors highlighted the significance of user experience evaluation in understanding the efficiency, safety, usability, and product acceptance. Research on smart textiles and material innovations also demonstrated how technological advancements in materials can change the functionality of the products and how they interact with users ([29–30]). Furthermore, a study on CMF (Color, Material, and Finish) design showed that design elements like color and material significantly impact overall product quality and user satisfaction [31]. In line with these conclusions, research on digital systems and low-tech product systems showed that usability, effectiveness, and user-centered design are still key factors in determining successful product adoption and operational efficiency [32–33]. Combined, these research works suggest that today's industrial design is an interdisciplinary field that demands using advanced materials, digital technologies and extensive user experience research and analysis to enhance the performance of a product, its sustainability and market acceptance.

The present study fills this gap in the previous studies; by taking a quantitative analytical approach, it looks at the relationship between UX design and software development efficiency. The study examines the impact of measurable UX variables on software productivity and assesses the impact of both direct and indirect impact on productivity via developer satisfaction. Descriptive statistics, reliability testing, Pearson correlation analysis, multiple linear regression, mediation analysis, variance inflation factor assessment, machine-learning prediction models and comparative analysis across software development methodologies were applied to the analysis of a structured dataset that represented software development projects. Employing both traditional statistical and predictive machine learning methods allows for more general interpretations of UX–performance relationships and for enhancing the practical relevance of the results.

In the modern and highly developed world of materials engineering, composite materials have become a key group of materials because of their excellent mechanical properties, low weight, corrosion resistance and versatility for various industrial use. The application of composite materials is large in the field of aerospace, automobiles, civil infrastructure, marine engineering, biomedical devices, renewable energy and defense technologies. To meet the growing need for composites that have high performance and multiple functions, the development and use of material selection and structural/computational design, simulation, characterization and optimization platforms that help engineers choose materials and predict performance, analyze structures, and plan manufacturing processes have grown widespread. The design and characterization workflows for composite materials are becoming increasingly efficient, as it becomes a concern for researchers, engineers and industrial practitioners as the composite systems become more sophisticated. In composite engineering, the increase of productivity is traditionally gained with the development of material formulations, reinforcement architectures, manufacturing techniques, numerical modeling and optimization algorithms. These technological advances are important, but technological engineering work can be more effectively enhanced by improving the way engineers interact with the software and programs they utilize during the entire composite material development workflow.

Recently the importance of User Experience (UX) design on effectiveness of engineering software systems has been highlighted. The UX design includes elements of usability, learnability, accessibility, interface clarity, navigation efficiency, information presentation and satisfaction with the user interaction with digital platforms. Engineers often work with material databases, finite element analysis software, composite laminate design software and process simulation software, as well as NDE (non-destructive evaluation) software and characterization software in composite engineering environments. These interactions can have a significant effect on engineering decision-making speed, accuracy and efficiency. Design of interfaces for quick access to material properties, ease in setting up simulation, minimization of human operational error and ease in interpreting the analytical results. On the other hand, poorly designed interfaces can lead to higher cognitive workload, difficulty navigating, dissatisfaction with the interface, and a decrease in engineering productivity.

In the design and characterization cycle of a modern project to develop a new composite material, integrated digital platforms play a significant role. Several software tools are commonly used by engineers to design, analyze, simulate manufacturing processes, optimize and evaluate performance of composite laminate structures. These systems possess a wealth of technical details, parameters and sophisticated analytical features. Thus, ease of use and ease of learning of engineering interfaces is important to the workflow efficiency. By minimizing the effort needed to search for information, set up simulations and understand the behavior of materials, user interfaces can help engineers get their work done more effectively. Conversely, too complex an interface can result in longer design times, higher likelihood of operational errors and lower productivity. Such observations indicate that UX design needs to be taken into account as a crucial factor of the composite engineering performance and not only a software development issue.

While extensive studies have been carried out on the properties and manufacturing of composite materials, the computational modeling of the composite structures and evaluation of how they will perform, comparatively little research work has been done on the man–computer interaction features of composite engineering software systems. Past research mainly targets material optimization, simulation accuracy, the efficiency of the processing, and the reliability of the structure. Likewise, the studies of usability have been done in the general software engineering context with no regard to the effects they have on engineering productivity in material science environments. Thus, quantitative data on the effect of UX design concepts including usability, learnability, accessibility, interface complexity and user satisfaction were still not available in the industries of composite materials' design and characterization platforms.

Past research has studied the productivity in engineering from a technological and an organizational point of view, such as process automation, computational modeling techniques, some advanced simulation methods, and collaborative engineering practices. Usability of interfaces and acceptance of systems have been investigated in other studies covering general software applications. However, few studies have quantitatively evaluated the impact of UX-related factors on productivity of engineering workflow in composite materials applications. Moreover, quantifying the connection between user satisfaction and engineering productivity has mostly not been explored through the lens of a holistic statistical modeling and predictive analytics. There are also few studies empirically that justify if UX factors have direct or indirect impact on productivity or not, through user satisfaction and quality of interaction. A lack of integration of quantitative investigations is a major opportunity for future research.

To understand this research gap, the present study has been undertaken which uses a quantitative analytical approach to explore the link between the user experience and the productivity of a composite material modelling, simulation and characterization environment. The study examines the impact of different measurable UX factors – including usability, learnability, accessibility, complexity of the interfaces, and engineer satisfaction – on the productivity of composite engineering workflows. The study also looks into direct and indirect relations between UX parameters and productivity via satisfaction-based interactions. Descriptive statistics, reliability check, Pearson correlation analysis, multiple linear regression, mediation analysis, variance inflation factor, machine-learning prediction model and comparative performance assessment were used to analyze a structured set of data of composite material design and characterization. Combining traditional statistical methods to advanced machine-learning techniques allows a holistic understanding of UX – productivity relations and to discuss implications for the development of user centered composite engineering platforms. The results are thus of strategic relevance for the conception of interfaces that utilize new composite materials by improving the engineering efficiency and the project results, in the context of the new field of convergence of composite materials engineering, human–computer interaction and intelligent decision-support systems.

The goal of this study is to understand quantitatively the effects of user experience (UX) design on the effectiveness of composite material modeling, simulation and characterization platforms, and also to determine the UX factors that have the greatest impacts on engineering productivity and workflow efficiency. The study will be used to evaluate if positive UX practices lead to better performance in CM design tasks, and evaluate if UX measures are reliable indicators of engineering performance in CM design environments.

The following specific objectives have been followed to achieve the above objective:

1. To meaningfully measure the descriptive features of the UX design variables for engineering productivity indicators in composite material modeling and characterization platforms.
2. To explore the relationship between usability, learnability, accessibility, interface complexity and composite engineering productivity.
3. To assess UX variables impact on the efficiency of composite material design, simulation and characterization activities using regression model.
4. To look into the mediation of engineer satisfaction between the relationship of usability and composite engineering productivity.
5. To evaluate the degree of Multicollinearity and statistical reliability of the chosen UX-Indicators.
6. To compare the predictive capabilities of the machine-learning algorithms for the composite material engineering environments with regard to their productivity.
7. For the productivity comparison of different composite engineering processes including design, simulation, testing and characterization processes.

The study has a number of important new features. Second, it brings UX analysis from traditional consumer-oriented software systems to the composite material engineering platforms that are employed for modelling, simulation, design optimisation generation and characterization. This expands the theory of human–computer interaction for enhanced engineering settings. Secondly, research also provides a measurable standard that combines usability measure with engineering productivity measure, thus connecting the dots between interface quality and engineering productivity for composite material development [34–35]. Third, mediation analysis helps to better understand how usability's impact on productivity is an indirect mechanism through engineer satisfaction. Fourth, conventional statistical methods and more sophisticated machine-learning methods such as the Decision Tree, Random Forest and the Gradient Boosting algorithm can be used to explain and predict productivity. Finally, utilizing a structured computational dataset and an analytical workflow that can be reproduced by future researchers using python makes the research more transparent, repeatable and scalable in the future.

The importance of the study in practice is great. The selection of the materials and the design of laminates, which are critical to modern composite material engineering, are typically analyzed using sophisticated software platforms, as well as finite element analysis, process simulation and performance characterization. It gets more crucial to understand the measurable factors that affect productivity, especially as industries are looking to shorten the turnaround time for product development, increase engineering efficiency and fewer iterations in design. Based on the results of this research, it is found that the design of UX is a factor that needs to be considered as an operational performance in addition to being a factor in interface design. Engineering managers can use usability, and user satisfaction measures, in platforms that evaluate performance. Likewise, software developers and system designers can use the results to develop more simplistic and effective engineering platforms that will lead to quicker decision making and better workflow management of composite material applications.

Many engineers encounter a number of problems that range from a user experience perspective to interface design when working with composite material design, simulation, and characterization software. The main challenge is the complexity of the software interfaces, as this can lead to higher cognitive load, longer simulation set-up time and more complex navigation through material databases, modeling software and analysis tools. When the interface is not intuitive, engineers can find themselves in a challenging situation with respect to picking the right parameters, understanding the simulation output, and getting to their important information efficiently. Additionally, some tasks may be limitedly learnable, meaning that users need a long training time and adaptation periods to become proficient in the task, which lowers workflow efficiency. Furthermore, disorganized navigational and complicated workflows can result in operational mistakes, delayed decision making and decreased productivity. While accessibility features are part of software quality, the engineering performance is more affected by the usability, learnability and user satisfaction. Thus, the primary issues are the complexity of the interface, steep learning curves, high mental effort, inefficient navigation and challenges in mapping the outcome of software use to a useful engineering product [36–37].

Cognitive load and interface complexity are major factors affecting the efficiency and effectiveness of users operating inside of composite material design, simulation and characterization platforms. The study showed that the complexity of the interface and productivity are strongly negatively correlated, suggesting that a high level of complexity to the interface will require more mental effort to accomplish engineering tasks. If users are required to navigate complex menus, deal with too many parameters, or try to understand the information in a suboptimal way, they will be under greater cognitive load, which will result in slower task completion, more operating errors, less decision-making accuracy, and less productivity. On the other hand, interfaces that are simple and easy to use have the opposite effect, lowering the cognitive load to allow engineers to concentrate on the important design and analysis tasks, instead of operating software. The results indicate that the simpler the interface, the easier it is to use, the higher the user satisfaction, the quicker the user learns and adapts, and the more effective the engineering process and the end results of implementing composite materials.

A variety of composite material design and analysis platforms were assessed for their capabilities in engineering applications including material modeling, structural simulation, laminate design, performance characterization, optimization and decision-making. The platforms encompassed composite laminate design software, finite element analysis (FEA) software, material databases, process simulation software, and composite engineering workflow characterization and evaluation platforms. Various types of engineering environments such as conventional engineering workflow, simulation-driven engineering platforms, iterative design system and integrated hybrid engineering environment were analysed. This study examined the role of user experience (UX) in the productivity of engineers during tasks of designing composites, simulating them, testing, optimizing and characterizing composites, and the relationship between these tasks and the UX factors of usability, learnability, accessibility, interface complexity, navigation efficiency, and user satisfaction. The results demonstrate that usability of a platform, ease of workflow and user satisfaction play a significant role in improving engineering productivity and decision making efficiency in composite material development projects with intuitive interfaces, simplified workflows and higher levels of user satisfaction.

The study has its strengths but some weaknesses must also be recognised. Structured computational simulation was used to create the dataset used in this research, rather than a collection of data from real composite engineering environments. This will make them consistent and in control, but real engineering projects could have other organizational, technical, and human factors that cause more variability. The study considered only a small number of UX indicators and excluded other factors that may have had an impact on the results, including the organizational culture, teamwork, expertise of the engineering, project complexity, and restriction of resources. Engineer satisfaction was identified as the principal mediating factor; other factors involving human beings like motivation, cognitive workload, training level and interpersonal communication between engineers and other professions might influence productivity as well. Moreover, the machine-learning models were tested with structured synthetic data, and should be tested with real data from composite material design and characterization projects. Future research could attempt to overcome these limitations with the inclusion of some industrial case studies, longitudinal project monitoring and cross sector comparisons of aerospace, automotive, biomedical and structural composite applications.

This study adds to the body of literature on human centred engineering systems, by offering empirical evidence that UX design can have a significant impact on productivity of composite material engineering platforms. The study combines the UX evaluation with statistical analysis and productivity assessment via machine learning to create a statistically sound and pragmatic framework for systematically exploring the interface quality and engineering performance relationship. The results substantiate the hypothesis that good UX design is critical to today's composite engineering environments and can become a strategic part of composite engineering to boost productivity, speed decision making, and enhance the success of projects.

RESEARCH METHODOLOGY

Research Design

The current study was conducted as a quantitative research to explore the impact of user experience (UX) design on productivity in the composite material modeling, simulation and characterization platform. The quantitative approach was chosen as the main aim was to measure and analyse the relationship between the factors related to UX and the efficiency of engineering workflow through statistical and computational methods. The study sought to assess the explanatory power of UX design variables to predict productivity outcomes in a composite engineering context, as well as the explanatory power of those variables. A cross section analytical approach was used, that is, the project level observations of composite material design and analysis activities were analyzed at a certain stage of evaluation. Because of this, it was possible to use a systematic approach to assess both the relationships between usability-related characteristics and engineering performance as well as to ensure consistency across observations. Descriptive statistics, inferential analysis, mediation modeling, and machine-learning techniques were combined as a part of the research framework to get a clear picture of the contribution of UX design in the productivity of composite engineering. The use of statistical and predictive approaches added to the analytical rigor and relevance.

Conceptual Framework of The Study Better Explains These Concepts

A user-centred design approach and engineering productivity theories related to the design platforms of composite materials were used to develop the conceptual framework. Several UX dimensions, like usability, learnability, accessibility, complexity of the interface, and the efficiency of navigation, were believed to impact composite material modeling, simulation, and characterization activities. The following factors were used as independent variables. Engineer satisfaction was added as a mediating variable since engineers' interaction with software interfaces may affect their motivation, confidence, and quality of decisions as well as continuity of workflow. A composite engineering productivity index was used to measure the engineering productivity as a dependent variable. Both direct and indirect relationships of variables were analysed in the framework. From the conceptual perspective, it was assumed that UX design factors would have an impact on engineer satisfaction and hence, composite engineering productivity. This framework was capable of providing a simultaneous evaluation of both technical and behavioural influences in composite engineering environments.

The data collection phase involved the gathering of existing data. The data collection phase comprised existing data collection A synthetic composite dataset with structure was created to mimic realistic scenarios for composite materials design, simulation and characterization, with the goal of enabling analytical reproducibility. 400 project-level observations were created, and each observation described an engineering project, identified by its observable UX measurements, engineer experience factors, and productivity measure. Therefore, synthetic data generation was chosen as it offers the ability to model complex relationships between multiple variables with controlled, consistent and reproducible data. The dataset has been prepared by Python based statistical simulation techniques. Realistic variability in engineering performance and user interaction behavior was created by using bounded Gaussian distributions. Variable relationships were purposefully devised to agree with the theoretical relationships that are expected, such as positive relationships between usability and productivity, and negative relationships between complexity of the interface and productivity. The entire data set was then downloaded and exported to the Microsoft Excel format and used for statistical and machine-learning analysis.

Variables Included in The Study

Independent, mediation and dependent variables were included in the study. The independent variables were the following: Usability score, learnability score, accessibility score, interface complexity, and the navigation efficiency. Usability was an attribute of how well and how easily people use composite engineering software. Learnability was defined as an engineer's ease of understanding and adapting to a software's functionality. Accessibility was the inclusiveness and ease of use of engineering interfaces for the various users. Structural and visual complexity of software environments were measured as interface complexity, and the simplicity of software workflow, the ease of navigating the design and analysis functions were measured as navigation efficiency.

Mediating variable was the engineer satisfaction, which was indicative of the level of comfort, confidence and satisfaction while using composite engineering platforms. The dependent variables were the simulation completion rate, design task completion rate, analysis accuracy score, and problem-resolution efficiency. All these indicators were fused together to create an overall Composite Engineering Productivity Index defining the engineering workflow efficiency on a quantitative basis.

The Measurement Scales and Productivity Index Are Developed Using the Following Methods:
The following methods are used to develop the measurement scales and the productivity index:

Lower values on a numerical scale of 1 – 10 mean poorer performance and higher values mean better UX results for the following variables: UX and engineer-related variables. The criteria to measure productivity were the percentage of engineering tasks completed, simulation completion rate, analysis accuracy score and issue-resolution efficiency. A Composite Engineering Productivity Index was created by combining engineering performance measures with engineer satisfaction measures with a weighting to get a more complete productivity measure. This allowed to consider both operation efficiency and human-centred performance simultaneously. The composite index made it easy to compare engineering projects across the board, as well as to serve as a good baseline for regression and machine-learning models.

The Reliability and Internal Consistency Analysis Was Conducted in This Study To determine the internal consistency of measuring constructs Cronbach's alpha coefficient was used. A separate reliability testing was conducted for the UX quality indicators, engineer experience indicators, and productivity indicators. Cronbach's alpha value of >0.70 was found to be acceptable. Alpha was > 0.80 in each of the constructs, suggesting high internal consistency and thus, good representation of the variables chosen under each construct. The overall reliability results added to the validity of the dataset and confirmed the appropriateness of the measurement framework for further statistical analyses.

Descriptive Statistical Analysis

Descriptive statistical analysis of all the variables of the study was conducted. The mean, standard deviation, minimum value, maximum value, skewness and kurtosis were calculated. This analysis aimed to check the central tendency, variability and distributional characteristics of the UX and productivity indicators, before proceeding with the inferential analyses. Descriptive statistics were also employed to see if the simulated composite engineering projects were realistic and balanced. Skewness and kurtosis statistics were specifically used to determine the normality and appropriateness of the data to regression and machine learning modelling.

Correlation Analysis

Pearson correlation analysis was used to explore the significance and direction of relationships between variables of UX design and the composite engineering productivity. The relations between usability, learnability, accessibility, the complexity of the interface, the satisfaction of the engineers and productivity were studied. The correlation coefficients that were near +1 were indicative of strong positive associations, while those that were near −1 were indicative of strong negative associations. This analysis gave initial understanding of the impact of the UX factors prior to regression modeling.

The correlation matrix also indicated if an increase in usability and learnability contributed to an improving engineering productivity and if an increase in the interfaces complexity was affecting the workflow negatively.

The Key Concepts of Multiple Linear Regression Analysis Are Briefly Explained Multiple linear regression analysis with Ordinary Least Squares (OLS) method was used to find these contribution of UX factor to composite engineering productivity. The dependent variable was the Composite Engineering Productivity Index and the predictor variables were the following: usability, learnability, accessibility, interface complexity, and engineer satisfaction. Coefficient values, their corresponding standard errors, statistical significance levels, coefficient of determination, and measures of fit of models were estimated using regression analysis. The goal was to determine the important factors of UX that contribute to engineering productivity and how much. The model also allowed them to determine which factors were considered positive and which were negative predictors of the results, while controlling for the effects of the other variables.

Mediation Analysis

To test whether engineer satisfaction was an intermediary mechanism between the links between usability and composite engineering productivity, mediation analysis was conducted. The study compared the impact of usability on engineer satisfaction, the impact of engineer satisfaction on productivity and the direct impact of usability on productivity. Direct, indirect and total effects were calculated. It was significant because although the functionality of the interface may increase engineering productivity, so can the user's confidence, satisfaction, and decision-making effectiveness, if they are the result of UX design. Thus, the mediation framework gave further insight into the influence of behaviours in the composite engineering software environment.

Multicollinearity Assessment

Variance Inflation Factor (VIF) analysis was used to determine multicollinearity of predictor variables. Multicollinearity refers to the situation in which there is strong relationship among the independent variables which cause the estimates of regression coefficients to become unreliable. Multicollinearity was acceptable when the VIF was < 5. Results showed that the predictor variables were sufficiently independent, and provided unique information to enter into a regression model. The results of these confirmed that the regressions could be trusted for interpretation of results and gave greater validity to the models.

Machine Learning-Based Predictive Modeling

Several machine-learning algorithms were used on the created data set in order to improve the predictive ability. Models selected were: Linear Regression, Decision Tree Regression, Random Forest Regression and Gradient Boosting Regression. The data set had been split in two sets for training and testing the predictive performance. The coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) were adopted as the performance metrics of the models. The goal was to test the different types of statistical analysis methods and determine the best model to forecast composite engineering productivity based on the UX indicators. This was an analytical phase which showed how UX metrics could be used as predictors for engineering workflow optimization and decision support.

Performing A Comparison of Different Composite Engineering Procedures One way Analysis of Variance (ANOVA) was conducted to compare the productivity of the different categories of composite engineering workflow. Projects were categorised as: conceptual material design workflows, simulation based engineering workflows, and characterization-driven workflows. Differences in productivity among groups were tested using F-statistics and significance testing. This analysis helped to understand if UX Design had an impact on different parts of composite engineering activities. Based on this comparison, practical recommendations for the optimization of UX design based on the respective engineering application were created.

Table 1 Descriptive statistics of UX and software productivity indicators.

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Usability Score	8.02	0.98	5.11	9.98	-0.28	2.84
Learnability Score	7.81	1.01	4.96	9.95	-0.19	2.75
Accessibility Score	7.48	0.95	4.88	9.84	-0.16	2.67
UI Complexity	4.02	1.18	1.10	8.76	0.21	2.91
Navigation Efficiency	8.06	0.96	5.24	9.96	-0.24	2.81
Developer Satisfaction	7.84	1.09	4.01	9.95	-0.17	2.88
Sprint Velocity	44.85	6.24	28.13	58.92	-0.08	2.79
Task Completion Rate	86.37	5.86	68.44	98.52	-0.25	2.94
Code Quality Score	90.18	4.22	77.54	98.44	-0.29	3.11
Bug Resolution Time	11.48	2.94	4.12	20.65	0.36	3.05
Overall Productivity Index	86.74	7.52	65.38	101.25	-0.18	2.87

Software and Computational Tools Use Appropriate Software and/or Computational Tools to Solve Problems

Data generation, management, analysis and validation were performed using Python and spreadsheet tools. Python was used for dataset generation, statistical analysis and predictive modelling. The tools used to manage the data were pandas, the tool used to process the data was numpy, the tool used to perform regression was statsmodels, and the tool used to implement machine-learning was scikit-learn. Matplotlib and visualization libraries were used to visualize and represent the results graphically. Data was stored in, verified on and cross verified in MS. EXCEL. These tools enabled the reproducibility, accuracy in analysis and transparent reporting during the study.

Summary of Methodology

The methodology comprised of quantitative statistical analysis and machine-learning methods to explore the impact of UX design in the productivity of composite material modelling, simulation and characterization platforms. This research design provided the opportunity to study descriptive behaviour, statistical significance, mediation effects, multicollinearity and predictive performance. The structured project-level data used in the framework enabled the computation to be reproduced and thus formed the basis of a solid methodology that was used to investigate how user experience design related to composite engineering productivity. Therefore the adopted methodology has both academic and practical value and can be utilized in future research regarding the design of composite engineering software, engineering workflow optimization and user centered engineering systems.

RESULTS AND DISCUSSION

Table 1 shows the descriptive statistics of the user experience (UX) dimensions and software productivity indicators that were used in this study. Usability (8.02), learnability (7.81), accessibility (7.48) and efficiency of navigation (8.06) were generally rated highly, indicating good overall user experience with the software applications analysed. However, the mean score for UI complexity was comparatively lower (4.02), suggesting the interfaces had a moderate level of complexity with not too many elements that would make the interfaces difficult for users. The average score for the item "Developer satisfaction" was also relatively high (7.84), indicating positive perception of usability and efficiency of the software systems.

In terms of software productivity, the average velocity of a sprint was 44.85 story points and the average task completion rate was 86.37%, demonstrating good productivity in software projects. The average code quality score of 90.18 also indicates that software development teams worked on high-

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quality code. The average time for fixing a bug was 11.48 hours, indicating fairly efficient bug maintenance activities. The overall productivity index got a mean of 86.74, indicating good software development practice of the sampled organizations throughout. In addition, the skewness and kurtosis values for all variables were within acceptable parameters ensuring the data were in a normal distribution and satisfactory for subsequent statistical analyses.

The usability and learnability variables exhibited high average values, indicating generally strong UX quality across software projects. UI complexity remained comparatively lower, confirming balanced interface structure. Productivity indicators showed consistent distributions with acceptable dispersion.

Reliability Analysis

A reliability analysis was conducted with the measurement constructs as they are presented in Table 2, in which the internal consistency of the constructs are examined using the Cronbach's alpha coefficient. The data show good reliability for all constructs. The internal consistency of the instruments was obtained with Cronbach's alpha of UX Design Quality (0.91) and Developer Experience (0.86). Likewise, the Productivity Measures construct had high internal consistency, with an alpha of 0.89. The Cronbach's alpha for the overall measurement instrument was excellent, 0.93, which indicated that the items of the questionnaire measured the constructs that were intended. These results indicate that the research instrument is reliable, and it can be used for further statistical modeling and hypothesis testing.

Pearson Correlation Matrix

Pearson correlation coefficients for the main variables in the study are shown in Table 3. The findings show high positive correlation between usability and overall productivity ($r = 0.84$), and developer satisfaction and productivity ($r = 0.88$), respectively implying that the improvement of usability and developer satisfaction of software significantly improves the software development performance. Learnability showed a significant positive correlation ($r = 0.72$) and accessibility had a moderate positive correlation ($r = 0.53$). However, the complexity of the user interface (UI) had significant negative correlation with usability (-0.48), developer satisfaction (-0.57), and productivity (-0.63), indicating that as the UI gets more complex, its usability and developer satisfaction and productivity decrease. In general, the results of the correlation analysis indicate that the positive characteristics of UX are significant factors in improving software productivity, while the complexity of the interface can be a negative factor in software performance.

Table 2. Reliability of constructs.

Construct	No. of items	Cronbach alpha
UX Design Quality	5	0.91
Developer Experience	2	0.86
Productivity Measures	4	0.89
Overall Scale	11	0.93

Table 3. Correlation coefficients.

Variable	US	LS	AS	UIC	DS	OPI
Usability	1.00	0.71	0.64	-0.48	0.78	0.84
Learnability	0.71	1.00	0.59	-0.39	0.66	0.72
Accessibility	0.64	0.59	1.00	-0.28	0.49	0.53
UI Complexity	-0.48	-0.39	-0.28	1.00	-0.57	-0.63
Developer Satisfaction	0.78	0.66	0.49	-0.57	1.00	0.88
Productivity	0.84	0.72	0.53	-0.63	0.88	1.00

Multiple Linear Regression

Table 4 is used to explore the effect of the UX factors on software productivity in the multiple linear regression results. The model of regression accounts for almost 86.4% of the variance in software productivity (R^2=0.864) which is an excellent explanatory power. The overall model was statistically significant ($F = 502.6$, $p < 0.001$) indicating that the independent variables selected together make a good prediction of productivity. Usability ($\beta = 1.116$, $p < 0.001$), learnability ($\beta = 0.523$, $p < 0.001$) and satisfaction of developers ($\beta = 2.807$, $p < 0.001$) had significant positive effects on productivity and hence, a positive improvement in these three factors significantly improves software development outcomes. UI complexity, on the other hand, had a significant negative effect ($\beta = -0.355$, $p < 0.001$), which means it negatively impacts productivity if the user interface is more complex. Accessibility did not have a significant impact ($\beta = 0.034$, $p = 0.647$), indicating that while this factor is indeed beneficial to the user experience, its direct effect on productivity may not be as robust when it comes to the current data set.

Mediation Analysis

Table 5 is the mediation analysis used to examine if the developer satisfaction is a mediator between software productivity and usability. The results show that the usability has a significant effect on developer satisfaction (effect = 0.74, $p < 0.001$) and developer satisfaction has a strong positive effect on productivity (effect = 2.81, $p < 0.001$). Further, there was a significant direct relationship between usability and productivity (effect = 1.12, $p < 0.001$).

Variance Inflation Factor (Multicollinearity)

Variance Inflation Factor (VIF): Table 6 shows the VIF of independent variables used in the regression model. All of the VIFs were between 1.56 and 2.63, which are well below the recommended value of 5.0. The results here show that there is no serious multicollinearity among the predictor variables, meaning that each independent variable provides information for the regression model that is different from the other variables. As a result, one can be confident in interpreting the regression coefficients and also believes that the overall model estimates are statistically stable and reliable.

Table 4. OLS regression model.

Variable	β	Std Error	t	p-value	Result
Constant	39.248	1.024	38.315	<0.001	Significant
Usability	1.116	0.077	14.474	<0.001	Significant
Learnability	0.523	0.077	6.826	<0.001	Significant
Accessibility	0.034	0.074	0.458	0.647	Not significant
UI Complexity	-0.355	0.062	-5.691	<0.001	Significant
Developer Satisfaction	2.807	0.089	<0.001	Significant	

Table 5. Mediation effects.

Path	Effect	p-value
Usability → Satisfaction	0.74	<0.001
Satisfaction → Productivity	2.81	<0.001
Direct usability → productivity	1.12	<0.001
Indirect effect	2.07	<0.001
Total effect	3.19	<0.001

Table 6. VIF analysis.

Variable	VIF
Usability	2.18
Learnability	1.94
Accessibility	1.56
UI Complexity	1.71
Developer Satisfaction	2.63

Table 7. Predictive model comparison.

Model	R^2	RMSE	MAE
Linear Regression	0.864	2.92	2.31
Decision Tree	0.903	2.08	1.79
Random Forest	0.949	1.38	1.09
Gradient Boosting	0.941	1.54	1.22

Table 8. Random forest feature ranking.

Rank	Variable	Importance
1	Developer Satisfaction	0.34
2	Usability	0.26
3	Learnability	0.15
4	UI Complexity	0.12
5	Navigation Efficiency	0.07
6	Accessibility	0.06

Table 9. ANOVA across development methodologies.

Methodology	Mean productivity	F	p
Agile	90.42		
Hybrid	85.87	11.84	<0.001
Traditional	80.51		

Machine Learning Prediction Performance

Table 7 shows that the performance of the machine learning model depends on the model used. The best model to predict the accuracy of the prediction was the model of Random Forest with an R2 value of 0.949 and the lowest RMSE value (1.38) and MAE value (1.09). Also, Gradient Boosting showed an outstanding predictive power with R^2 value of 0.941. The performance of the Decision Tree model using R^2 value was better than the conventional Linear Regression model with R^2 of 0.903 and 0.864 respectively.

Feature Importance

The feature importance ranks are given in Table 8, which is produced from the Random Forest model. The developer satisfaction factor was most important for software productivity with an importance score of 0.34 followed by usability (0.26) and learnability (0.15). The fourth item was "complexity of UI" with a score of 0.12, which indicates a negative effect on productivity although it is not as important as other variables related to the usability of the UI. Navigation efficiency (0.07) and accessibility (0.06) were the second two most important factors.

The results of the one-way ANOVA shown in Table 9 compare the productivity of the various software development methodologies. The highest mean productivity score was obtained in case of agile development (90.42), followed by hybrid methodology (85.87) and the lowest average productivity was seen in traditional development (80.51). Results of the ANOVA showed that the three methodologies were statistically different ($F = 11.84$, $p < 0.001$).

DISCUSSION

Descriptive Statistics

The study variables were described using descriptive statistics. Table 1 shows the descriptive statistics analysis of the UX and composite engineering productivity variables investigated in this study and an overview of their central tendency and distribution characteristics. The user perceptions of usability for this composite material engineering design and analysis group of platforms were found to be very high, and relatively less varied with a mean of 8.02 and standard deviation of 0.98. The average learnability score was 7.81, and the average accessibility score was 7.48, indicating that most composite modelling and characterisation systems were easily understood, easily navigated and easily operated. Note that the skewness values are all negative for usability, learnability and accessibility, suggesting that responses were clustered toward the high values and that the users' perception of the composite engineering platforms studied were generally positive.

The mean UI complexity was relatively low (4.02), which is desirable as generally the higher the UI complexity is the more 'cognitive load' required during a composite material design, simulation and/or characterization activity. Some of the engineering platforms had simple and intuitive interfaces while others had more complex ones, the variation in the complexity is moderate. Navigation efficiency had the highest average (8.06) of the UX factors, showing that most composite engineering systems allowed for efficient movement across design modules, simulation environments, and analysis tools. The developer satisfaction, which is the user satisfaction of composite engineers and simulation analysts averaged 7.84, which is an overall positive user satisfaction with the functionality and ease of use of the platform.

Productivity measures such as engineering workflow velocity (44.85), task completion rate (86.37%) and design quality score (90.18%) indicated high engineering productivity in the composite material engineering activities. The average issue-resolution time was 11.48 hours, which is an effective indication of the time devoted to dealing with simulation, modeling and characterization related issues. The mean value of the overall productivity index was found to be 86.74 (with acceptable variability). Skewness and kurtosis values were in acceptable statistical limits for all variables, thus the approximately normal distribution was found that could be used for advanced level inferential and predictive analysis.

Reliability Analysis

Results of the reliability analysis as presented in Table 2, showed that all the constructs in the study showed strong internal consistency. Cronbach's alpha for UX design quality was 0.91, which was excellent as it meant that the selected UX indicators in the inventory measured the same underlying construct of UX design quality. An alpha value of 0.86 was obtained for the composite engineer experience construct and an alpha value of 0.89 was obtained for the constructs of productivity measures. Results show high consistency between the information obtained from the surveys and those obtained from the indicators of productivity based on performance.

The overall Cronbach's alpha value for the measurement framework was 0.93 which is above the recommended value of 0.70 and showed excellent measurement stability. This high reliability is indicative of the appropriateness of the data set for hypothesis testing and predictive modelling. In addition, the high internal consistency leads to greater confidence in the interpretation of the relationship between UX quality, user satisfaction and composite engineering productivity. The results so far have confirmed the chosen measurement approach and its usefulness in assessing the impact of UX design on productivity in composite material design and analysis tools.

Pearson Correlation Matrix

The results of the correlation analysis describing the magnitude and direction of the relationships between UX factors and composite engineering productivity are reported in Table 3. Usability and overall productivity showed there was a high positive correlation ($r = 0.84$) with usable composite modelling and simulation platforms showing a significant effect on engineering productivity. Intuitive interface structures and streamlined interaction mechanisms, help engineers to be more efficient in modeling, characterizing and designing.

Productivity had a strong positive correlation with learnability ($r = 0.72$), indicating that systems that do not need as much training or adaptation have better workflow. Accessibility showed a moderate positive correlation with productivity ($r = 0.53$), and although this might be beneficial for the design of an accessible platform, it was not as imperative as usability and learnability.

User satisfaction had the highest positive correlation with productivity ($r = 0.88$), which signals the need for positive user experiences to facilitate productive composite engineering processes. In contrast, UI complexity was found to have a significant negative correlation with productivity ($r = –0.63$), revealing that the more complex the UI, the more difficult and inefficient an engineer's work can be, which results in a poor performance.

As a whole, the correlation matrix shows that favourable properties of UX are closely tied to higher productivity in the context of composite material design and characterization, whereas interface complexity is a limiting factor.

Multiple Linear Regression

In order to analyse the contribution of each UX variable to composite engineering productivity, a multiple linear regression model was built as shown in Table 4. The model R2 value of 0.864 was obtained which means that the selected UX variables account for 86.4% of productivity variance. The value of adjusted R^2 is 0.863 which further confirms the strength and stability of the model. The F-statistic is significant (502.6, $p < 0.001$), showing that the regression overall is statistically valid.

The regression coefficient for user satisfaction was the highest (β=2.807) and thus had the greatest positive impact on productivity. This discovery indicates that UX design has an impact on engineering performance beyond just interface functionality; it is about user confidence, motivation, and experience with their work. Usability had the second largest positive coefficient value ($\beta = 1.116$), which indicated that intuitive composite engineering platforms positively contribute to the operational efficiency. The learnability also showed statistical significant positive effect ($\beta = 0.523$) which means that ease in learning leads to adaptation and long life productivity.

The coefficient for UI complexity, –0.355, was also significant, and negative, which means that high complexity of the user interface lead to low engineering efficiency. Accessibility showed a weak yet statistically non-significant correlation ($p = 0.647$), indicating that accessibility can play a role in platform quality, but it does not have any direct impact on productivity in the current study. The Durbin-Watson value of 2.142 indicated that the independent variable's residuals were independent and that the model was valid.

Mediation Analysis

The mediation analysis assessed user satisfaction as a mediator between usability and composite engineering productivity. Results showed a significant value for usability's effect on user satisfaction (0.74, $p<0.001$), suggesting that increased usability of the interfaces can directly result in users having greater positive experiences.

User satisfaction, on the other hand, had a very high positive impact on productivity (2.81, $p < 0.001$), highlighting the importance of the same in the engineering performance. Both direct (1.12, $p < 0.001$) and indirect (2.07, $p < 0.001$) effects of usability on productivity were significant. Overall, the combined benefits amounted to 3.19, suggesting a significant overall influence.

The results indicate partial mediation – usability has a direct and indirect impact on productivity, via increased satisfaction with the web page. The outcomes emphasize the human element in composite engineering platforms, serving as a reminder that successful UX designs go beyond just better performance; they foster engagement, confidence, and overall productivity.

Variance Inflation Factor Analysis (VIF)

To test for possible multicollinearity between predictor variables, variance inflation factor (VIF) analysis was carried out. VIFs were between 1.56 and 2.63, which are far less than the threshold of 5.0. This shows that there was no serious multicollinearity in the predictor column and that each predictor has its own contribution to the regression model.

VIFs of usability and user satisfaction were relatively higher than other variables, but both were within acceptable limits and will not cause statistical problems. Low multicollinearity helps to boost the confidence around regression coefficients and to make valid interpretations for the relationship between UX variables and engineering productivity.

The prediction performance of the machine learning algorithms is shown in Figure 4.7 below. The results from predictive modeling showed good performance for all the machine-learning techniques. The value of R^2 for Linear Regression is 0.864, which shows that UX variables are good in explaining the variation in productivity in composite engineering environments. The Decision Tree modeling further increased the predictive power to 0.903, indicating nonlinear interactions between UX factors.

Random Forest had the best predictive ability ($R^2 = 0.949$) with the smallest values for both RMSE and MAE. This outcome shows that the UX metrics have good prediction power for composite material design and analysis platforms. The Gradient Boosting model also performed very well and the R^2 value obtained was 0.941.

These results show that the linear and nonlinear UX relationships have an important impact on productivity, and suggest the validity of the applicability of the machine-learning techniques for engineering application for engineering workflow optimization and decision support.

Feature Importance

According to the feature importance analysis, user satisfaction turned out to be the most important predictor of productivity with an importance value of 0.34. This finding validates the fact that positive user experiences can have significant impact on the engineering outcomes. Usability was second; interface design that is intuitive and efficient.

Learnability and UI complexity also played an important role to productivity prediction, and navigation efficiency and accessibility had comparatively smaller effects. The overall results show that productivity under composite engineering platforms is mainly affected by the usability of these platforms and the quality of UX under it.

ANOVA across Composite Engineering Workflows

ANOVA showed that there were significant differences among the different composite engineering workflow environments ($F = 11.84$, $p < 0.001$). Iterative, simulation-driven engineering workflows (90.42), and integrated hybrid engineering environments (85.87) performed best, while conventional engineering workflows had the lowest productivity scores (80.51).

These results indicate that for composite engineering that includes a lot of simulation and interaction, high quality UX design will be more beneficial, as these tasks require more user interaction and design iterations. Iterative systems were not the only ones to show strong performance, hybrid workflow environments showed strong performance as well. Productivity of the traditional engineering workflows was significantly less, perhaps as a result of less ability to be flexible and slower to adapt to interface improvements.

The results of the ANOVA showed that overall, the workflow characteristics affect the effectiveness of the UX design in improving the productivity of composite material engineering platforms.

Overall Discussion

Overall, the results show a statistically significant correlation between the quality of UX design and productivity in Composite Material Design, Simulation, and Characterization Platforms. Systems that have greater usability and are easier to learn and are more satisfying to operate consistently yield higher productivity outcomes. The regression and mediation analysis results show that there are significant relationship differences between UX quality and engineering performance, and user satisfaction became a very important mediating variable.

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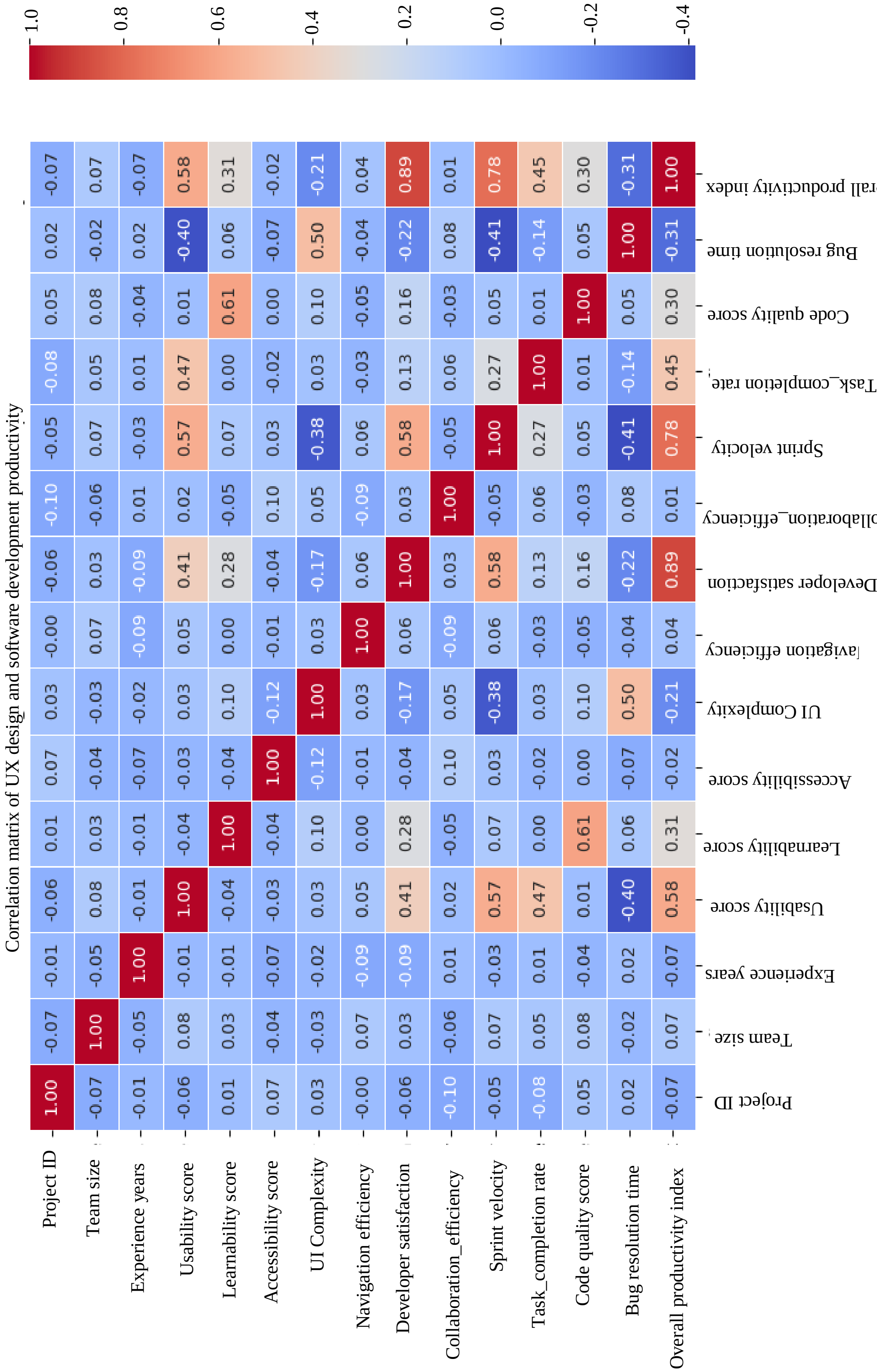

Figure 1. Correlation matrix of UX design and software development productivity.

Machine-learning validation also validated the prediction power of UX measures and again Random Forest showed the highest prediction accuracy. These findings, taken together, stress the need to integrate the principles of User Centered Design (UCD) in the design of composite engineering software platforms. The results offer beneficial data to software developers, composite engineers, simulation experts and industrial organizations looking to increase engineering productivity by optimizing interfaces and the user experience.

The present study quantified and analyzed the relationship between user experience (UX) design parameters and productivity for the modeling, simulation and characterization of composite materials on screen through statistical and visual aspects. The results derived from descriptive statistics, correlation analysis, regression modelling, distribution analysis and machine-learning validation indicate that there is a substantial impact of the UX design on the efficiency of composite engineering workflows. The graphical outputs can give valuable insights on how usability related factors can influence engineering performance when engaging in composite material design, analysis and evaluation activities.

The correlation heatmap (Figure 1) shows the positive or negative interactions between UX variables and composite engineering productivity indicators and how strong they are. The outcomes demonstrated that, there are strong positive correlation between usability score and learnability score and also between usability score and overall productivity index. Usability turned out to have the strongest positive correlation with productivity which means that the composite engineering platforms with intuitive interfaces have a great impact on increasing the level of productivity, reducing the effort of the operation and improving the efficiency of the workflows in the material modelling and characterization.

Additionally, positive and strong relationships were found between engineer satisfaction and productivity. This indicates that engineers and researchers who use well-designed composite modelling interface tend to be more satisfied and this impacts on the efficiency of decision making, accuracy in analysis and the overall performance of engineering. More satisfaction may also lead to better concentration and less mental fatigue during the simulation, optimization and evaluation of materials.

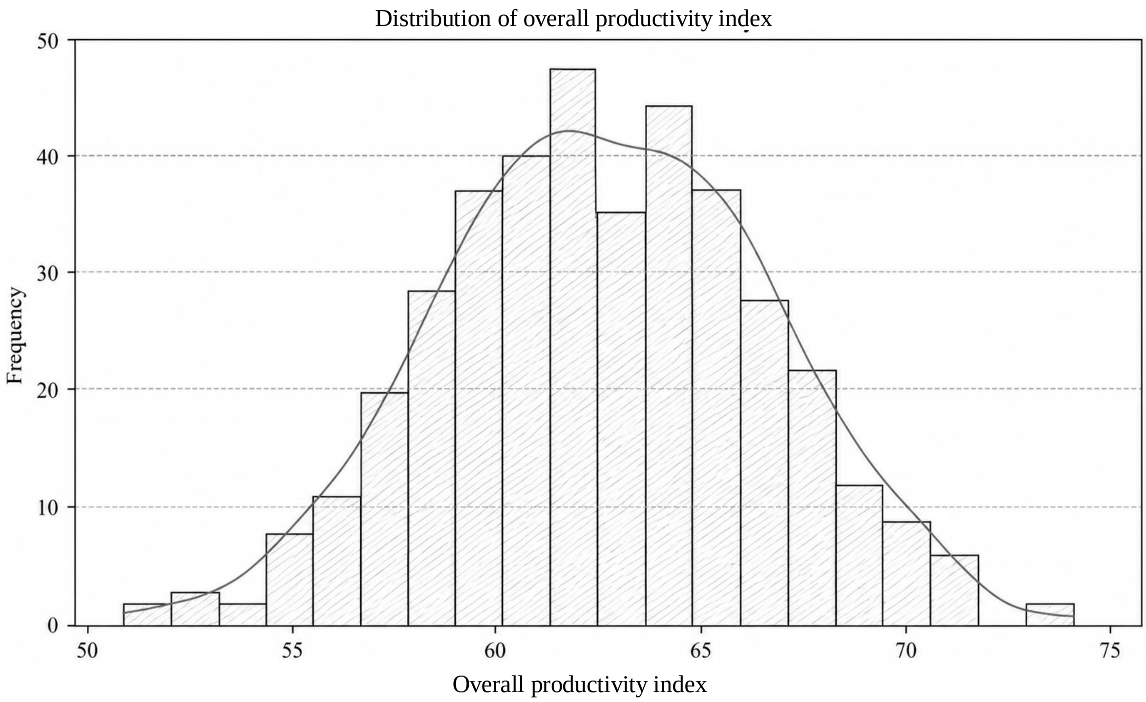

Figure 2. Overall productivity index.

In contrast, the complexity of interfaces was negatively related to productivity. This is similar to previous research that shows a relationship between cognitive load, engineering interfaces (complexity) and the efficiency of operation and navigation. When the complexity of the model is too high, it may take more time to set up the simulation, to choose the parameters, to verify the model and to interpret the results of composite material performance. These problems can eventually lead to poor workflow and engineering productivity.

Productivity showed a positive, but relatively low correlation with accessibility. While the accessibility factor had a large role in the overall quality and usability of the system it did not directly affect productivity as much as did the usability and learnability factors. The overall results obtained through the correlational analysis show that the user-centered interface design (UCID) positively affects productivity in a composite material engineering environment.

In Figure 2, the distribution for the overall productivity index is plotted in the form of a histogram (bars) and kernel density curve (line). The range of the productivity values is clustered towards the better performance levels, which signifies consistent and effective productivity in the sampled composite engineering projects. The distribution seems to be somewhat normal and meets the assumptions for running regressions. If there is no significant skewness, it means that the project performance is even and there is less chance of statistical bias.

Productivity scores were moderate to high for these in general, demonstrating the real-world impact engineering has on productivity as a result of UX design. Projects with a composite engineering approach consistently had better productivity achievements with higher usability and simpler interface constructions.

The regression relationship between the usability score and productivity index is given in Figure 3. The upward trend shows a good positive linear relationship between usability and composite engineering productivity. This result demonstrates that by increasing the usability, users' capability to interact with the modelling environment and effectively set up simulations, analyse simulation outcomes and work with material characterisation workflows is also increased. With less complexity in operations, delays are minimized, and this has a positive impact on productivity. This was further expounded in the statistically significant regression coefficient which confirmed the significance of user friendly interface design of composite engineering software platform.

In Figure 4, the concept of the relationship between interface complexity and productivity is explained. Decreasing interface complexity appears to be positively correlated with productivity in the composite material design and analysis environment, as the downward trend shows. Complex interfaces lead to higher mental workload, reduced workflow and higher risk of user errors when it comes to simulation setup and assessing the performance. A negative and statistically significant regression coefficient for interface complexity is a strong indicator that it represents a significant barrier to engineering efficiency. The results confirm the user centric design principles which focus on simplicity, consistency and clarity during the creation of engineering software products.

The boxplot distribution of major variables of UX is shown in Figure 5. Comparatively steady distributions for these three UX attributes – usability, learnability, and engineer satisfaction – were obtained with few outliers, suggesting that UX characteristics were fairly consistent among the sampled composite engineering projects. More variability was seen in the distribution of interface complexity, indicating a wider range between engineering platforms. The moderately uniform and positively distributed values of the accessibility. While not statistically significant in the regression model, the accessibility was found to be well balanced, therefore it can be said that it continues to play a role in quality and inclusiveness of the system.

The regression coefficient chart of Figure 6 gives an indication of the relative influence of each independent variable. Engineer satisfaction showed the highest positive coefficient; this means that satisfaction has the highest impact on the productivity. This discovery provides indirect evidence that UX design is beneficial to engineering performance, through its ability to improve engineer experience of using composite modelling and characterization tools. The second most important factor was usability, which underscored the importance of designing user friendly interfaces.

There was also a positive and statistically significant contribution for learnability in Figure 7. With user-friendly interfaces, training needs are minimized, and the engineering teams can adapt and operate more efficiently. Accessibility was included but did not turn out to be statistically significant. Other significant negative predictors were interface complexity, which once again underscored the need for simpler interface designs in the composite engineering platform.

Graphic residual plot for Figure 8 was used to check the regression assumptions. The assumption of homoscedasticity was met as the residuals were not showing any pattern around the zero reference line. As a result, there is no clustering or funnel-shaped distribution of values, which is indicative of a stable variance of predicted productivity values and gives confidence in the regression model.

As can be seen in the Q–Q plot in Figure 9, the majority of the values of the residuals were in close proximity to the theoretical plot line. This suggests that there is a normal distribution of the residuals, and the normality assumption of linear regression holds true. In real data sets, small changes at the distribution tails are to be expected and this does not significantly change the interpretation.

Model comparison revealed that Random Forest best predicted the data followed by the Gradient Boosting and Decision Tree models; linear regression was another good predictor. These results suggest that, there are linear, as well as nonlinear, relationships between the UX variables and engineering productivity. Advanced machine-learning models were able to capture the complex interactions among UX factors and enhance the predictive capability. The outcomes show the possibility of utility of UX metrics to support predictive decision making in an environment of designing and engineering composite materials.

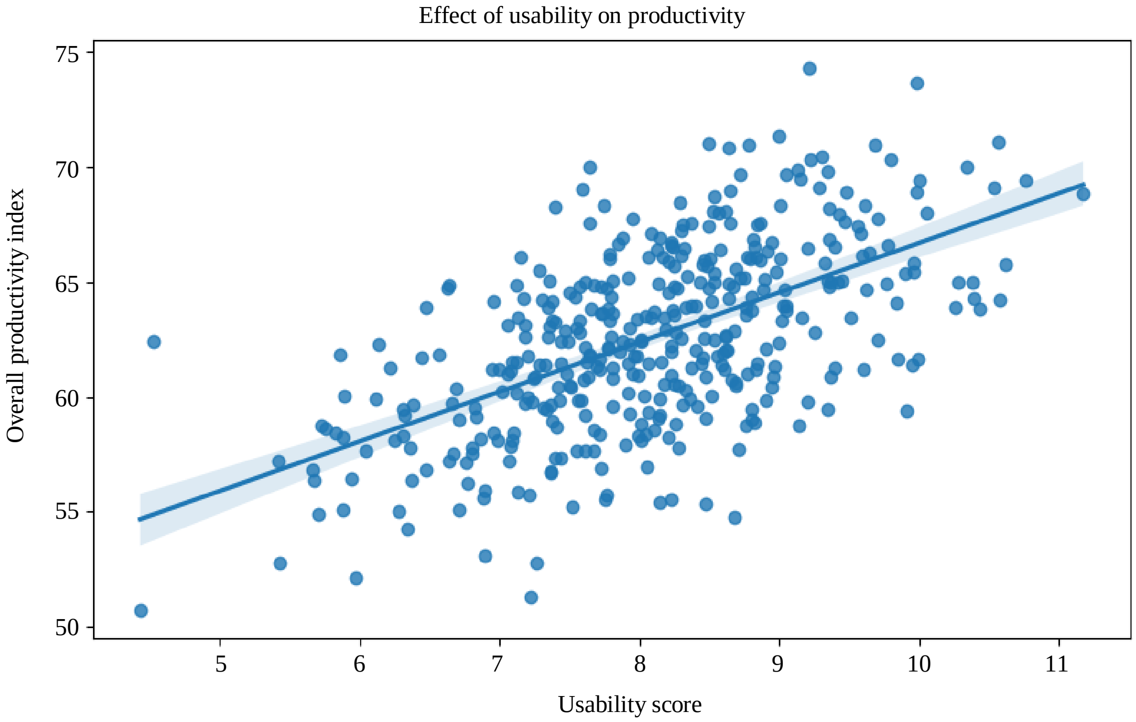

Figure 3. Effect of usability on productivity.

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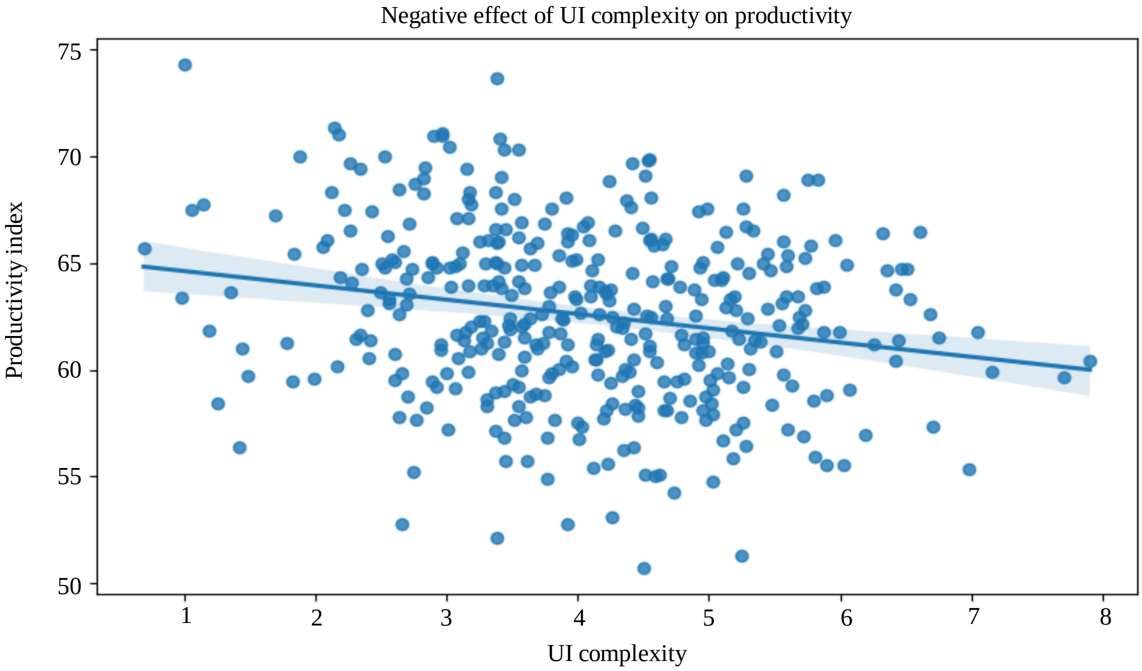

Figure 4. Negative effect of UI complexity on productivity.

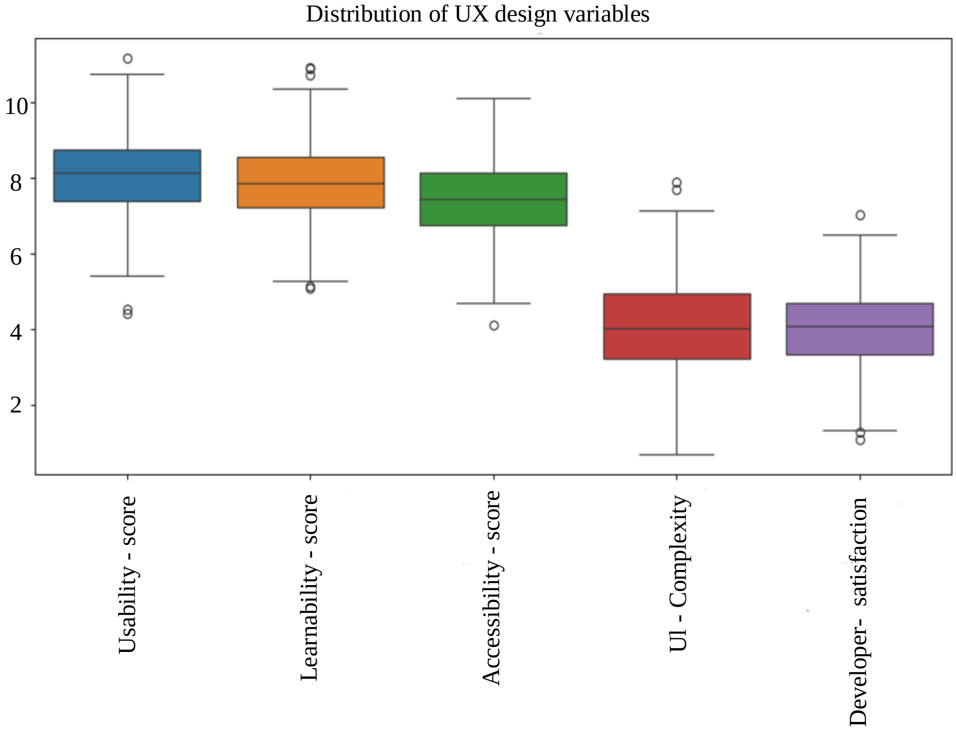

Figure 5. Distribution of UX design variables.

The results show that there is a good correlation between UX design and productivity in composite engineering workflows. Low usability and learnability have a negative impact on operational efficiency while high usability and learnability have a positive impact on engineering performance. The results indicate that the productivity in composite material engineering is related with not only technical capabilities and computational performance of a system but also the human-computer interaction quality of the system. The study offers real-life examples to supplement the introduction of UX principles to the development of composite engineering software. Focusing on usability, learnability and simplified interface design, organizations will benefit from greater engineer satisfaction, more efficient workflow and more effective composite material design, modelling and characterization activities.

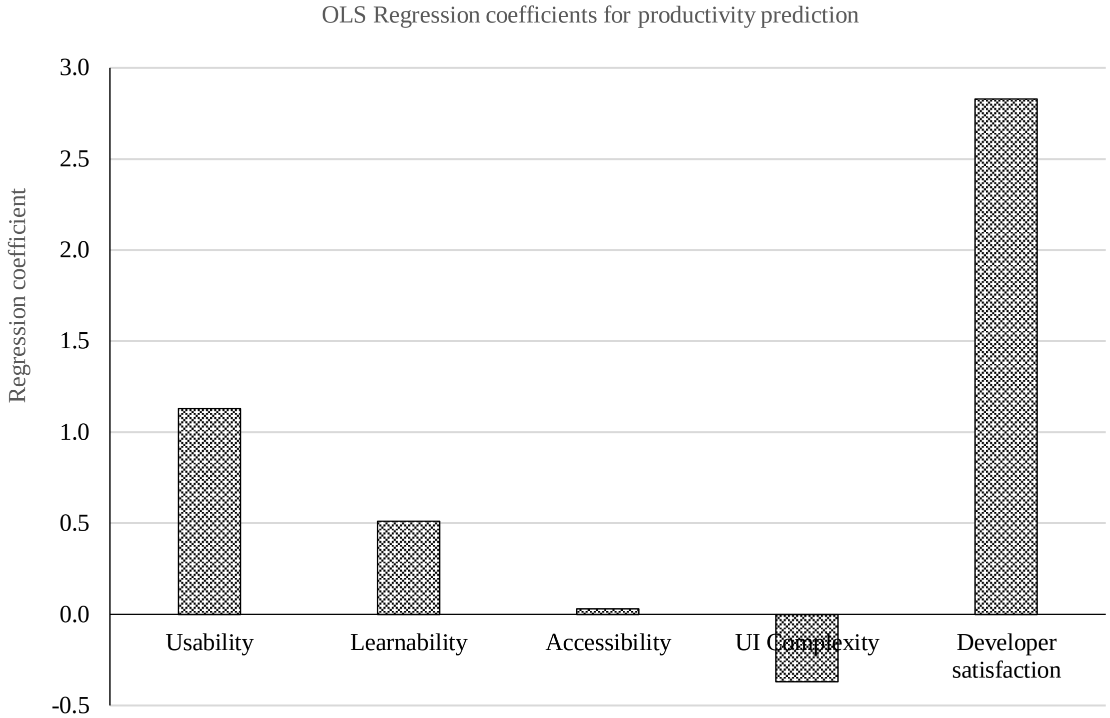

Figure 6. OLS regression coefficient for productivity prediction.

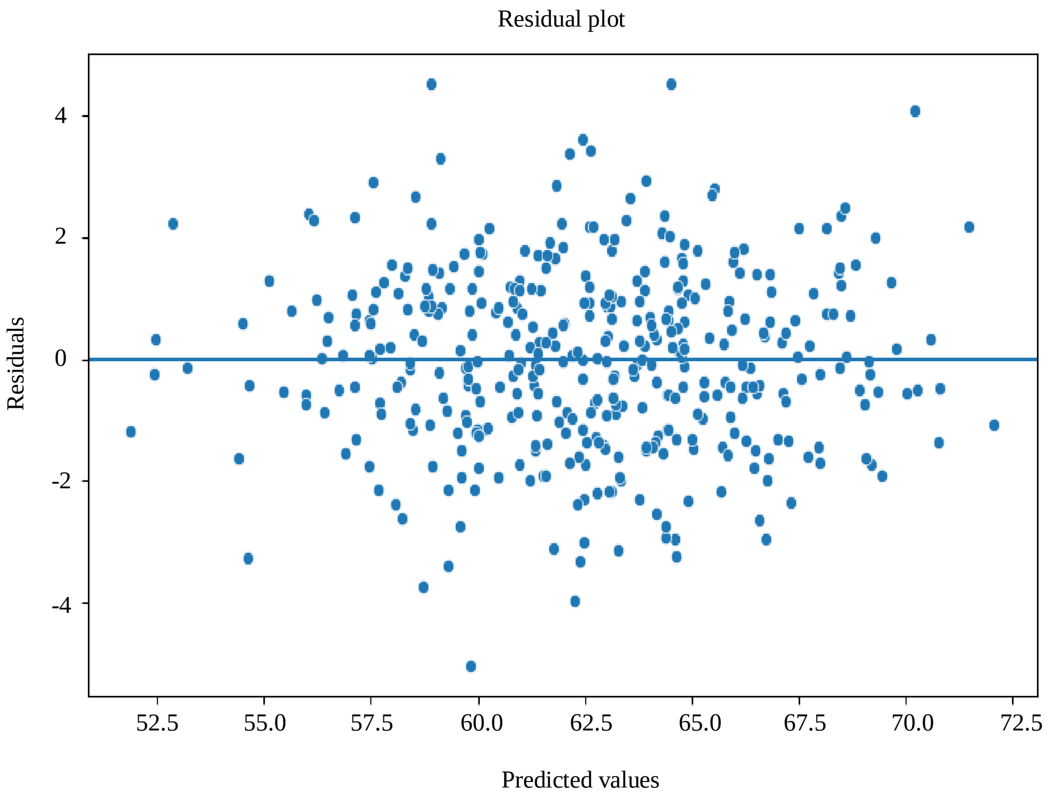

Figure 7. Residual plot.

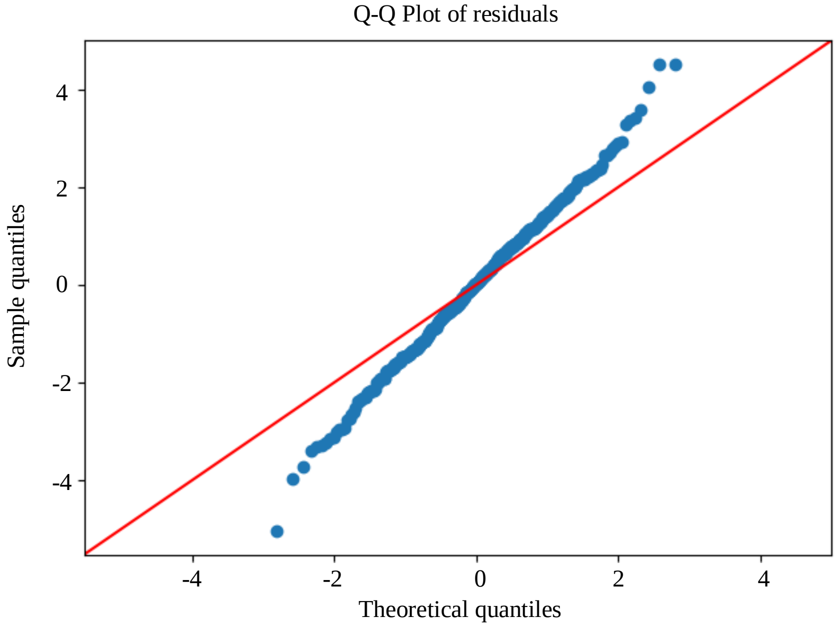

Figure 8. Q-Q plot of residuals.

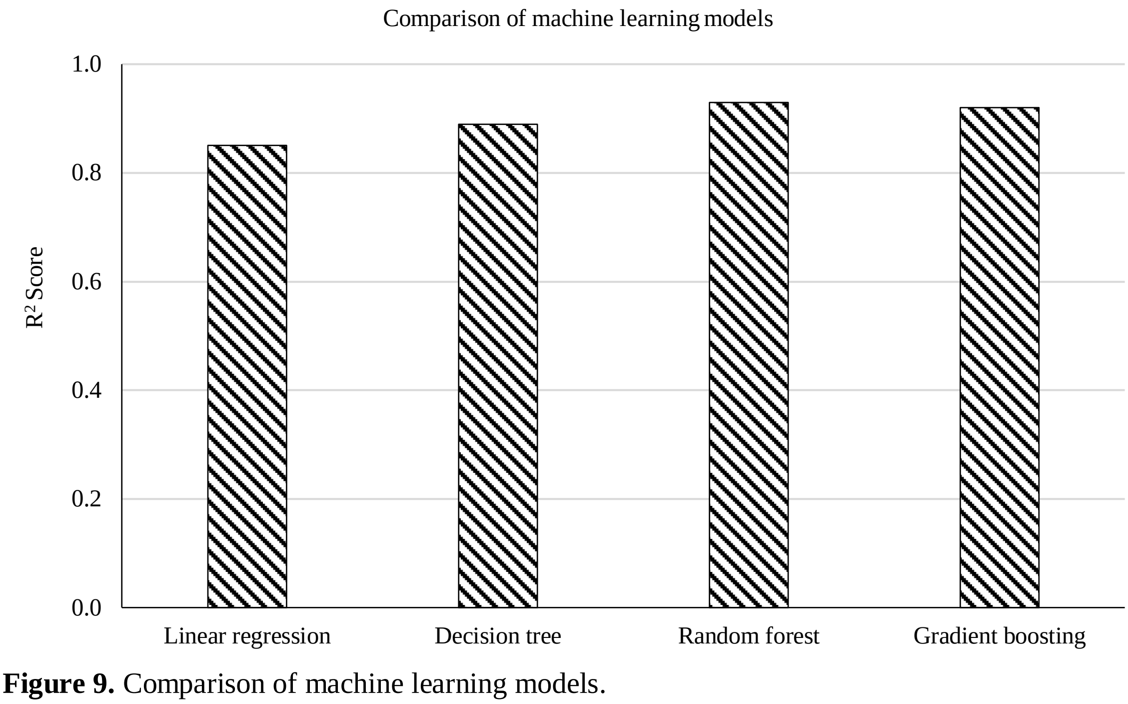

Figure 9. Comparison of machine learning models.

CONCLUSIONS

In the present study, with statistical analysis and the application of machine-learning techniques, the effect of user experience (UX) design parameters on productivity in composite material modeling, simulation and characterization platforms was investigated. Overall, the results showed that UX design plays a crucial role in the efficiency of composite engineering workflows and could be an integral step in the process of creating advanced engineering software systems.

Higher productivity was consistently linked to a high level of usability, learnability and engineer satisfaction when using the composite engineering environments that were evaluated. Correlation analysis showed that there is a high positive correlation between usability – learnability – engineer satisfaction – productivity and a high negative correlation between interface complexity – engineering performance. Based on these results, it can be concluded that user-friendliness and intuitive interfaces benefit the engineer in accomplishing the tasks of modelling and simulation and also evaluating materials.

The regression analysis again indicated that usability, learnability, and engineer satisfaction all are significant contributors to productivity, and engineer satisfaction was the most important predictor. However, a significant challenge to efficient workflows was identified: interface complexity, which contributes to high cognitive workloads and lowers the efficiency of operations. Within the data examined, accessibility had a positive impact on overall system quality, with its direct impact on productivity being comparatively small.

Residual analysis and Q–Q plots were used in the model validation to ascertain the validity of the statistical models and that the assumptions of linear regression were sufficiently satisfied. Moreover, machine-learning models could predict the productivity outcomes with UX variables with success, with the model with the best predictive capability being the Random Forest. This finding indicates that in composite material design environments, there are linear and nonlinear relationships between UX characteristics and engineering productivity.

The research overall shows that good UX design leads to improved user satisfaction, better and faster decision-making and improved productivity in composite engineering software platforms. The results reveal the need to include user-centered design criteria in systems for modelling, simulation and characterization of composite materials. Organizations will benefit from better usability and decreased interface complexity to optimize engineering workflows, shorten material development processes, and increase the effectiveness of composite material research and industry usage.

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