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IDENTIFYING THE EFFECTS OF IMMERSION ON DESIGN FOR ADDITIVE MANUFACTURING EVALUATION OF DESIGNS OF VARYING MANUFACTURABILITY

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ABSTRACT

The demand for additive manufacturing (AM) continues to grow as more industries look to integrate the technology into their product development. However, there is a deficit of designers skilled to innovate with this technology due to challenges in supporting designers with tools and education for their development in design for AM (DfAM). There is a need to introduce intuitive tools and knowledge to enable future designers to DfAM. Immersive virtual reality (VR) shows promise to serve as an intuitive tool for DfAM to aid designers during design evaluation. The goal of this research is to, therefore, identify the effects of immersion in design evaluation and study how evaluating designs for DfAM between mediums that vary in immersion, affects the results of the DfAM evaluation and the mental effort experienced from evaluating the designs. Our findings suggest that designers can use immersive and non-immersive mediums for DfAM evaluation without experiencing significant differences in the outcomes of the evaluation and the cognitive load experienced from conducting the evaluation. The findings from this work thus have implications for how industries can customize product and designer-talent development using modular design evaluation systems that leverage capabilities in immersive and non-immersive DfAM evaluation.

Keywords: Additive Manufacturing, Design for Additive Manufacturing, Cognitive Load, Virtual Reality

NOMENCLATURE

AM Additive Manufacturing
ME Material Extrusion
CAE Computer-Aided Engineering
VR Virtual Reality

1. INTRODUCTION AND MOTIVATION

The continued global expansion of the additive manufacturing (AM) industry by nearly 7.5% to roughly $12.8 billion in 2020 [1] along with 2x forecasted growth worldwide to roughly $37.2 billion in 2026 [2] shows the growing significance and demand for AM in the product development market. Experts project that by 2030, manufacturing of less critical spare parts will be primarily driven by AM and a significant amount of AM products will leverage capabilities in multi-material fabrication and product development with embedded electronics [3]. Although the demand for AM-driven product development continues to grow, there is a deficit of designers and engineers [4] in the workforce suited to meet this demand. This deficiency in in-house AM and design for AM (DfAM) knowledge is a barrier to the integration of AM in the industry [5, 6] inhibiting industries from innovating with AM. It is, therefore, imperative to prepare the future workforce with the skills and knowledge in AM and DfAM to meet this growing demand for AM-driven innovation in product development.

The typical considerations for DfAM contrast against the standard design for manufacturing and assembly (DfMA) considerations due to the unique design freedoms and restrictions offered by AM technologies; this contrast thus requires a new wealth of knowledge tailored to support industrial DfAM practices [7, 8]. Focus on developing AM and DfAM capabilities through design-centric resources [9–11] and accessible in-depth process-centric education [12] can empower designers and engineers in the future AM workforce [13] to creatively leverage AM in product development [14]. Past work supports designers by providing tools [9, 15], frameworks [10], and design guides and heuristics [11, 16] to improve DfAM-focused product design exercises. Such tools are useful aids for designers when designing and evaluating production using AM, but they are limited in their medium of presentation and utility: specifically, they are limited to non-immersive sketching or computer mediums. The medium of design evaluation, however, influences the results of the evaluation [17–20] and presents different levels of difficulty and mental load [21] during the evaluation exercise. It is, therefore, important to consider how the medium through which designers access and apply design and process-centric AM knowledge affects their DfAM development and product design capabilities.

Spatial and psychomotor characteristics of the media and tools strongly influence design evaluation exercises [17] and increasing the immersion of the medium shows improvements in the

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outcomes of a design evaluation exercise [19, 20, 22–25] while minimizing the limitations from non-immersive mediums [18]. The immersion of a medium, therefore, has a strong influence on design evaluation and the mental effort experienced from the evaluation exercise; however, limited work [26] in the fields of AM and DfAM investigates how the medium in which a designer conducts DfAM evaluation affects their evaluation. No identified work in AM and DfAM literature compares the effects of immersion between virtual and in-person mediums or investigates the effects of immersion on cognitive load from a design evaluation. This research, therefore, aims to address this gap in the literature and analyze and compare the use of different immersive mediums as tools in DfAM evaluation; the mediums compared are Computer-Aided Engineering (CAE), Virtual Reality (VR), and the real physical medium. There is an opportunity to improve DfAM evaluation exercises and designer talent to enhance industrial product design capabilities. The goal of this research is to, therefore, identify the effects of immersion in the design experience and study how evaluating designs for DfAM in mediums of varying immersion affects the results of the evaluation and the mental effort experienced to evaluate designs. The findings from this work can have significant implications for how future designers are trained in AM and DfAM to meet the AM-driven product development demands in the workforce.

2. RELATED WORK

Immersion in virtual environments aims to give users a "vivid illusion of reality" [27, 28] and is measured in comparison to the real and physical world having the highest levels of immersion. As such, virtual realities are often a technological collaboration of immersion and presence [28, 29] to surround a user in a digital space that mimics visual, auditory, and other sensory elements of the physical reality. VR is hence measured in terms of the extent to which a virtual environment can surround users to simulate immersion and presence. Therefore, traditional computer displays typically fall under non-immersive VR while head-mounted displays (HMDs) fall under immersive VR [29, 30]. However, for the sake of clarity, this research reinterprets these definitions with the following distinctions: CAE = non-immersive virtual medium (i.e., a flat computer screen), VR = immersive virtual medium (i.e., an HMD), REAL = immersive physical medium (i.e., the physical world). The goal of this research is to identify how the differences in immersion between CAE, VR, and REAL mediums impact the results of a DfAM evaluation and the cognitive load experienced from the evaluation. The remainder of this section highlights past work to provide insight into the challenges with using traditional manufacturability evaluation methods for DfAM evaluations and emphasizes the need for AM and DfAM tailored tools (Section 2.1). It also analyses the existing applications of immersive virtual mediums in product design evaluation to support the use of VR for DfAM evaluations (Section 2.2).

2.1 Tailoring design for manufacturability evaluation in AM-driven product design

Traditional DfMA aims to integrate design considerations driven by the manufacturing processes to realize designs into physical products. Doing so bridges the gap between design and manufacturing engineers [31] to reduce development time and cost, and increase performance, quality, and profitability in the product development cycle [8]. DfMA-focused tools and techniques are, therefore, commonplace resources to help designers to consider DfMA in product development. Similarly, DfAM needs to be considered when developing products powered by AM; however, due to the various design freedoms and restrictions offered by AM technologies, the design knowledge, tools, and methodologies are different from traditional DfMA [8, 32]. Traditional DfMA tools, knowledge, and design considerations thus may not apply when designing for production through AM. Therefore, the analytical tools, training programs, and design frameworks for DfAM need to advance simultaneously to support designers for AM-driven product innovation in the workforce.

Research into automated AM analysis presents promising avenues for industries to use in their digital thread [33–35] by empowering designers with relevant analytical and design tools. As automation in digital manufacturing improves and provides expedited and easy-to-use design evaluation options to leverage within the AM digital thread, there will be a demand for new knowledge and skills in digital manufacturing [36] to enable designers to think "generatively" and design for AM [3]. In addition to focusing on automation in AM, it is thus essential to invest in developing tools and resources that aid designers in learning and applying DfAM to suitably support parallel advancements in AM. These tools and resources need to enable designers to operate with both design and process-centric AM knowledge and thus help them creatively leverage the range of AM capabilities in product development. As such, past work provides different worksheets [9, 15, 37, 38], methodologies [10], and design heuristics [11, 16] as tools for designers to use during product development that provide insight on when, where, and how to consider AM. While such existing tools offer extensive capabilities to evaluate different DfAM design elements, they are limited to process-dependent guidance tailored to specific AM processes [9, 15, 16, 38]. There is a need for a consolidated tool that covers a range of DfAM metrics and offers a process-agnostic DfAM tool when conducting user-based DfAM evaluation.

Past work leverages different DfAM tools and principles to investigate the outcomes from user-based design evaluation [26, 39, 40]. Generally, such work focuses on restrictive DfAM metrics. Ostrander et al. [26] and Budinoff and McMains [40] studied how DfAM analysis tools help users identify quality issues and potential print failure in designs prior to manufacturing. Scheele et al. [39] evaluated AM process capabilities by leveraging users' DfAM intuition to assess manufactured part quality through restrictive DfAM metrics. However, this past work relies on existing DfAM tools that are limited to non-immersive or textual mediums of utility due to their inherent benefits during design [18]. Limited work i) investigates alternate mediums of presenting designers with DfAM knowledge [41], ii) studies the application of virtual and immersive technology, such as VR, to support DfAM [26], or iii) quantifies the mental load caused by different media during design evaluations [21]. There is, therefore, a gap in existing knowledge supporting the field of DfAM that explores how design evaluation and cognitive load are impacted by the medium of evaluation. Understanding how the medium of evaluation affects a DfAM evaluation may help improve a designer's AM product design capabilities.

2.2 Comparing virtual and real, immersive and non-immersive mediums in engineering and design

Designers need to supplement their traditional DfMA tools with intuitive tools that improve their DfAM capabilities; however, existing DfAM tools heavily rely on non-immersive mediums where the lack of immersion may prove limiting during DfAM evaluation. Unlike traditional manufacturing that can leverage traditional media, such as 2D sketches and computer drawings, AM requires digital 3D model data for the eventual realization of a design. Immersive design environments like VR, therefore, make intuitive sense to investigate as tools for DfAM evaluation due to the streamlined nature of introducing complex virtual models into an immersive virtual space. Past work supports this intuitive investigation into VR to serve as a design evaluation medium tailored for AM and DfAM.

Designers need to prototype and evaluate their designs to innovate during product development. Traditionally, designers leverage physical models and prototypes to visualize and identify the issues and improvements to address in their designs. Doing so can boost design performance [42] by rectifying flaws in the designer's mental models [43]. However, repeated and extensive use of physical prototypes fabricated through traditional manufacturing processes can be expensive and time-consuming [44, 45]. With the growth of AM technology, physical prototyping can be more feasibly considered as a method to conduct design evaluation. However, an AM prototype is directly dependent on the digital input [44], which requires designers to be trained in DfAM to minimize build failures and strengthen their understanding of restrictive DfAM [14]. Therefore, *virtual* prototyping may avoid some of the costs, limitations, and challenges with physical prototyping [44, 45]. Since AM relies on virtual models and digital manufacturing information, virtual prototyping is an inherently appealing approach during AM product development.

Computer-aided technology enables virtual testing and prototyping that can be applied to various product design, engineering, and learning requirements [12, 46–48]. While non-immersive virtual tools offer numerous benefits for designers, research shows that adding immersive elements can improve the design experience and its outcomes [20, 23–25, 27, 29]. As Buxton [17] summarizes, this is because the characteristics of the media, tools, and human-related factors, such as spatial perception and reasoning, and psychomotor skills, strongly influence the design evaluation exercise. Ibrahim and Rahiman [18] consequently reflect this summary and show that conventional sketching is a useful tool to highlight design concepts, but is limited when analyzing complex designs. Conversely, while computer-aided design is advantageous for detailed engineering, it was found to limit intuitive ideation. These observations emphasize the need for tools that offer enhanced spatial and psychomotor capabilities while providing efficient design and prototyping capabilities. Past work indicates that immersive technologies like VR can consolidate the benefits of conventional sketching and CAE while avoiding their limitations, to offer fast and fluent design conceptualization and analysis of complex designs.

Advancements in immersive technology are driving industry use of VR in product design, engineering, and manufacturing to support decision making and enable innovation [49]. This trend is significant enough that educational analyses suggest that virtual and real platforms will power future hybrid learning opportunities [50]. Existing research provides insight into the effectiveness and applicability of VR in industry and education [27, 29, 49]. Specifically, past work indicates that VR shows promise in developing declarative and procedural-practical knowledge [27], cognitive skills (e.g., understanding spatial and visual information), psychomotor skills (e.g., visual scanning or observational skills), and affective skills (e.g., controlling responses to challenging situations) [29]. Additional observable benefits of VR include: i) allowing designers to better perceive the fit of UI elements and estimation of the model dimensions [22], ii) identifying more errors and defects in 3D models when compared to CAE evaluation [20, 23], iii) making fewer mistakes in procedural assembly tasks [24] when compared to REAL product assembly, and iv) reducing task completion times when compared to both CAE and REAL [24, 25] conditions. Furthermore, past work suggests that designers experience differences when using VR over CAE as affected by the design complexity of their products [19, 22] where studies reported that models with a higher design complexity might benefit from review in VR than in CAE.

While these benefits of VR to a designer's product design abilities are key motivators for this work, it is also important to understand how challenging designers may find experiences when working across different mediums. One metric to measure this challenge is cognitive load, which quantifies the mental effort experienced to navigate or accomplish a task or action. Past work suggests that cognitive load may be influenced by immersion depending on the manual operations performed for task completion and the range of precise motor skills required to complete different tasks [51–56]. Specifically, there is an influence on cognitive load as the difficulty of processing task-related information and performing manual operations changes between low difficulty [51, 53, 55] to high difficulty [51, 52, 54, 56].

The literature strongly supports the potential benefits of immersion and VR in design evaluation. Limited work, however, explores these effects to specifically support DfAM [26]. Additionally, no known literature offers guidance on the cognitive load experienced by designers from their DfAM evaluation exercises across mediums of different immersion. The collective knowledge of how the immersion in a designer's product design and evaluation environment affects their DfAM evaluations and cognitive load can be leveraged to further improve industrial product design processes and better train and equip designers for the AM-driven product demands in the workforce.

3. RESEARCH QUESTIONS

Based on this previous work, the goal of this research is to analyze the effects from the differences between immersive (i.e., VR and REAL) and non-immersive evaluation conditions (i.e., CAE) on design evaluation (as measured by DfAM score, evaluation time, and evaluation confidence) and cognitive load (as measured by self-reported values). With this scope in mind, this research explored the following key research questions:

RQ1: How do the differences in immersion between CAE, VR, and REAL mediums affect the DfAM evaluation results for designs of varying manufacturability?

We believe that the evaluation through VR and REAL conditions will yield scores significantly closer to expert-reviewed scores, significantly faster evaluation times [26], and significantly higher reported confidence values than will the evaluation through the CAE condition; however, we do not expect significant differences between the two immersive conditions. This is expected due to the effects from the varying capabilities offered by the conditions when evaluating designs: capabilities such as interactivity, immersion, psychomotor coordination, and spatial perception and reasoning [17]. Additionally, changes in design complexity can influence the evaluation and performance outcomes [19, 22] when considered alongside the effects of immersion.

RQ2: How do the differences in immersion between CAE, VR, and REAL mediums affect the cognitive load experienced when evaluating designs of varying manufacturability?

We believe that as the difficulty of design evaluation operations changes due to the change in immersion, the VR and REAL experiences will require significantly less mental effort and will yield lower reported cognitive load values than will the CAE experiences; however, we do not expect significant differences between the two immersive conditions [51, 55]. This is expected due to the effects from the varying capabilities offered by the conditions which affect the difficulty of evaluating the features of the designs for manufacturability within the environmental restrictions. These effects are expected by virtue of the changes in difficulty of processing task-related information and performing manual operations changes between low difficulty [51, 55] to high difficulty [51, 52, 56] with the change in immersion.

4. METHODOLOGY

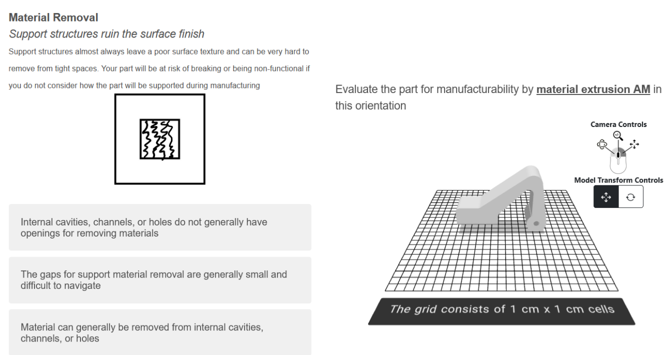
The goal of this research was to identify the effects of immersion on DfAM evaluation and experienced cognitive load when evaluating designs of varying manufacturability. This research, therefore, studied the experiences of novice designers within different mediums when they evaluated different designs for manufacturability with ME. Participants in this research were second and third-year undergraduate students recruited from an engineering design methodology course at an R1 university. Volunteers were first informed of their rights and options as per IRB protocol before conducting the study. Those who opted in to participate were provided an online Qualtrics survey that they completed on their PCs. Each participant was randomly assigned to one of the three conditions (i.e., either CAE, VR, or REAL). Balancing the number of data points between the three conditions was also handled automatically by the survey. During the study, participants shared their interest and motivation levels in learning and using AM, as well as their awareness of AM, material extrusion (ME), and design for ME (DfME) before they conducted the design evaluations for the study (Section 4.1). They then completed three design evaluation exercises one at a time (Section 4.2) and reported the cognitive load they experienced from evaluating all the designs (Section 4.3). A participant's design evaluation was measured by three metrics: i) the design's DfAM score, ii) the time taken for the evaluation, and iii) the confidence of the evaluation. The DfAM score was measured by adding scores from eight metrics where each metric was evaluated on a 3-point likert scale. Each design was thus scored between 8-24 points with a higher score suggesting a higher recommendation for manufacturability by ME. Cognitive load was measured by self-reported mental effort exerted during the experience. This section discusses how the designed experimentation measured these metrics to address the proposed research questions and further elaborates on the specifics in the overall experimental procedure.

4.1 Assessing the participants' backgrounds

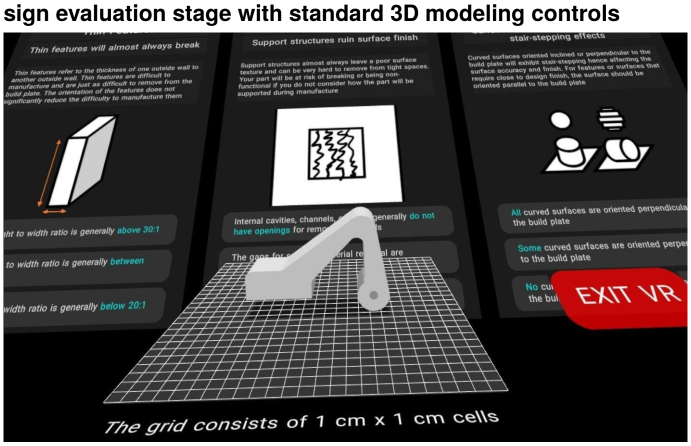
Participants first shared their interest and motivation regarding learning about AM and using AM. They indicated their agreement to the posed inquiries on interest and motivation on a 5-point likert scale that ranged from strongly agree to strongly disagree. They then shared their awareness of the overall AM technology. This data indicated their general experience working with their interpretation of AM and its design and manufacturing practices. They then shared their awareness specifically with the ME process and DfME practices. Awareness in AM, ME, and DfME was also recorded on a 5-point likert scale that covered identical options in each topic: i) never heard or learned about the topic, ii) had some informal knowledge in the topic, iii) had some formal knowledge in the topic, iv) had lots of formal knowledge in the topic, or v) was an expert in the topic. Comparing this data with the data on their general awareness of AM indicated the depth of awareness participants generally had with the AM technology, including the range of AM processes and their relevant design considerations. Collectively, the data on interest and motivation and AM, ME, and DfME awareness helped strengthen the statistical analysis on the results of the design evaluation and cognitive load. Before proceeding to the design evaluation exercise, participants in the CAE and VR conditions also shared their comfort levels in working with or interacting with 3D models (i.e., virtual objects) within their specific conditions. Participants in the REAL condition were not asked for their comfort levels.

4.2 Conducting design evaluation

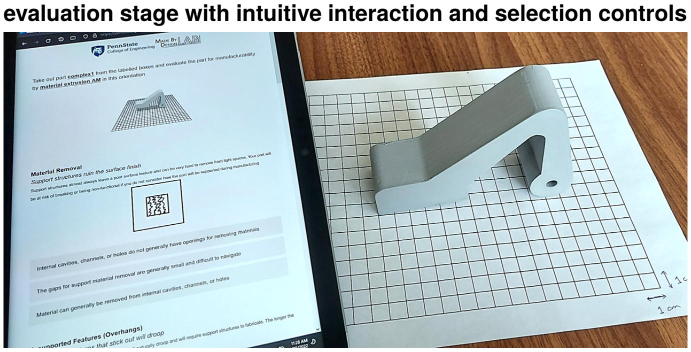
After providing information on their background, participants were directed to the design evaluation exercise. The experimental design for the part evaluation exercise across all the conditions gathered information on the evaluated DfAM score, the time taken for evaluation, and the confidence of the evaluation with logistical requirements in setup, required hardware, and adjustments to the study, tailored to the needs and constraints for each condition. Participants assigned to the CAE condition were directed to the design evaluation exercise in the survey on their PCs. Those assigned to the VR and REAL conditions were directed to designated study zones where they were provided the equipment and tools needed to complete the exercise. Participants in the VR condition were given Oculus Quest 2 VR headsets and controllers and directed to the design evaluation exercise on the Oculus browser. Participants in the REAL condition were directed to a table with the physical parts where they continued the design evaluation exercise on their devices. The virtual designs for the CAE (Fig. 1a) and VR (Fig. 1b) conditions included virtual parts, tools, and instructional information to help participants gauge scale and interact with their environment. The design of the REAL condition included physical parts, tools for measuring scale, and digital instructions for the exercise. The physical parts were manufactured using ME and underwent multiple post-processing cycles of coating with primer and sanding to minimize any visible indications of the original fabrication process.



(a) The CAE setup provided the worksheet side-by-side to the design evaluation stage with standard 3D modeling controls



(b) The VR setup provided the worksheet in front of the design evaluation stage with intuitive interaction and selection controls



(c) The REAL setup provided the worksheet in front of the design evaluation stage with the scale and orientation information

FIGURE 1: Showcasing the design evaluation setup for each condition to highlight the experimental design

In each condition, participants were instructed to evaluate the designs for manufacturability in a functionally constrained orientation as shown in Fig. 1 and were informed that the designs were to be manufactured using the ME process and hence to be evaluated for manufacturability for this specific AM process. They were allowed to freely interact with the parts and environment to the extent permitted within the given design evaluation medium. These interactions included picking up, rotating, and moving the parts to get a good view of the design and did not include re-scaling or digital enlarging capabilities.

During the evaluation exercise, participants used the provided worksheet [57] to evaluate a design using eight distinct process-agnostic metrics consolidated from work by Booth et al. [9] and Bracken et al. [15]. These metrics covered material removal, unsupported overhangs and bridges, self-supporting features, cross-sectional features parallel to the build plate, thin features, and surface accuracy of curved surfaces. Each metric was evaluated on a 3-point likert scale that was identical to a low-medium-high scale for evaluating quantities, thus, allowing participants to score a design between 8-24 points with a higher score suggesting a higher recommendation for manufacturability by ME. They were not informed of the scores they evaluated for the designs and hence were not given explicit feedback on their evaluation. They only saw the three options for each metric in the worksheet and were instructed to select the option that best fits the design they were evaluating. The summed scores for the designs were calculated later during the data analysis. Participants concluded one evaluation by filling out the entire worksheet and reporting their confidence in their evaluation of the design. They completed the entire exercise by evaluating three out of the five possible designs highlighted in Fig. 2, one at a time.

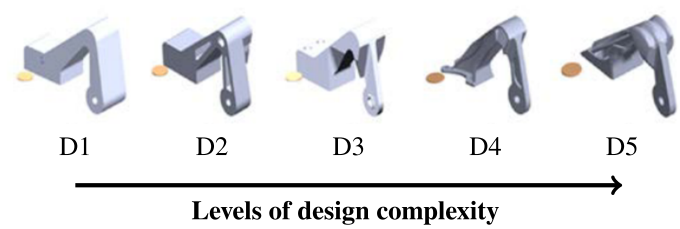


FIGURE 2: Showcasing the designs used in this research in the order of increasing design complexity [26]

Providing only three designs from Fig. 2 minimized the effects of survey fatigue thereby focusing on the cognitive load directly impacted by the exercise of evaluating designs within their assigned condition. The order of the designs presented was determined from a Balanced Latin Square that counterbalanced the participant pool to account for immediate sequential or carry-over effects [58]. Participants were only given designs listed in the first three columns in the 10x5 counterbalanced table. Doing so still honored the principles of the counterbalancing approach while addressing the concerns with survey fatigue. Multiple participants received the same order of designs, however, each order from the counterbalanced table was assigned to a participant randomly and the overall distribution was balanced by the survey.

4.3 Reporting experiential cognitive load

After completing the design evaluation exercise, participants reported their cognitive load using the Workload Profile Assessment (WPA) tool [59] by reporting the mental effort they exerted during the experience. The tool's high sensitivity when compared to the Subjective Workload Assessment Technique and the NASA Task Load Index [60] and its non-intrusive nature, when compared to other multidimensional subjective workload assessment instruments, provide strong support for its use in this study. Participants scored each of the eight workload profile dimensions (i.e., the perceptual, response, spatial, verbal, visual, auditory, manual, and speech) between 0 and 10 to represent their exerted mental effort. Each participant received a textual and audio description on each workload profile dimension to review, along with an example of each dimension applied in practice. This ensured consistency with how participants assessed their cognitive load and assigned quantitative values to each dimension.

5. RESULTS

This research collected 114 data points that were evenly distributed across the three conditions (CAE = 39, VR = 38, REAL = 37). Further breakdown of the data within each condition is listed in Tables. 1 and 2 show that each design (i.e., D1-D5) was presented evenly across the conditions, and the ordered set of designs presented was also evenly distributed (with the exception of the ordered set 541 in CAE and VR).

TABLE 1: Breakdown of the frequency of evaluation of each design within each condition

	D1	D2	D3	D4	D5
CAE	23	26	25	21	22
VR	21	23	24	24	22
REAL	23	21	22	22	23

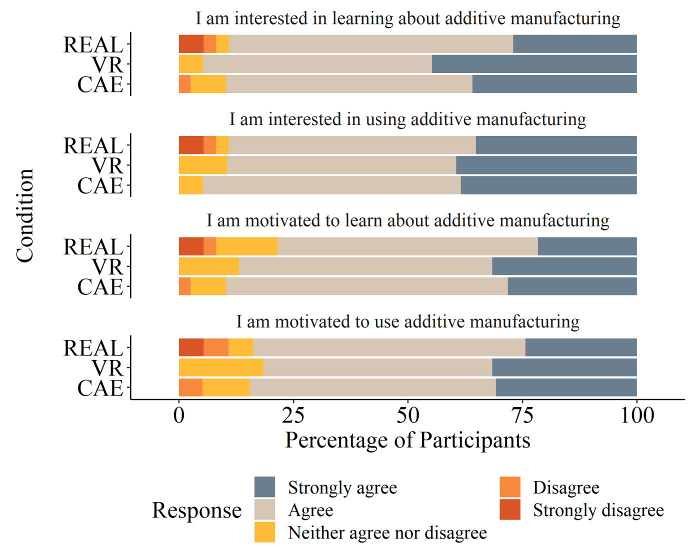
TABLE 2: Distribution of ordered sets of designs participants received within each condition (NOTE: ordered set 125 indicates that participants saw D1, D2, and D5 in that order)

	125	152	213	231	324	342	435	453	514	541
CAE	5	4	4	5	4	4	4	4	4	1
VR	3	4	4	3	5	4	3	5	5	2
REAL	4	3	4	4	3	3	4	4	4	4

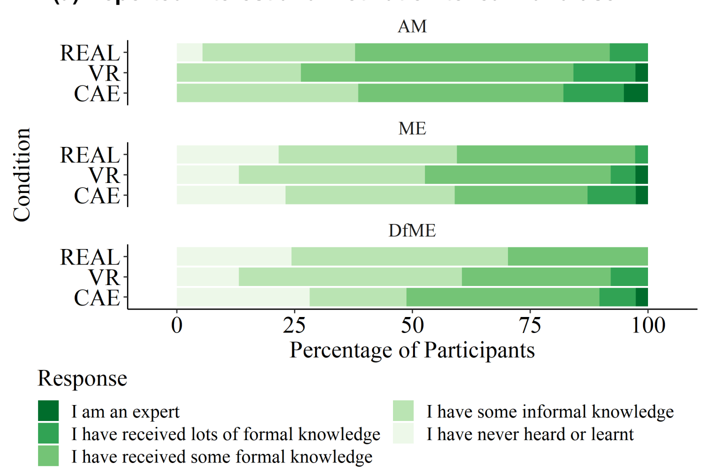
The even distribution of data across the conditions, designs, and ordered sets minimizes the effects of skewed data and strengthens the statistical analysis of the data on design evaluation and cognitive load. This research collected demographic data, design evaluation data, and cognitive load data and reports this collective data and the results from its analyses while maintaining all outliers. To account for the complexity of the experimental setup and the presence of multiple dependent and independent variables in its statistical analysis, this research uses linear regression modeling (lm) for the demographic and cognitive load data and linear mixed-effects regression modeling (lmer) for the design evaluation data. A 95% confidence interval was used to determine statistical significance (i.e., $p < 0.05$). The assumptions for linear regression and linear mixed-effects regression modeling were checked for violations using the Peña and Slate [61] and the Loy and Hofmann [62] procedures respectively. This research did not find any observable violations and relies on the acceptable range for the robustness of lms and lmers in its reported findings. Therefore, the statistical analyses in the following sections provide support from the participant demographic data (Section 5.1) to highlight the findings from the design evaluation exercises to address RQ1 (Section 5.2) and the reported cognitive load to address RQ2 (Section 5.3).

5.1 Demographic analysis of the participant pool

Demographic data collected from the participants (Fig. 3) strengthened support for the effects of experimental factors on the later observed results in design evaluation and cognitive load, by accounting for the effects from the participants' backgrounds on the observed results.



(a) Reported interest and motivation to learn and use AM



(b) Reported prior awareness in AM, ME, and DfME

FIGURE 3: Showcasing the collected demographic information for the participant pool highlight

Regressing the interest and motivation levels on the centered condition (CAE= -0.5, VR= 0, REAL= 0.5) showed no observable significant difference between the three conditions in interest and motivation (for interest to learn AM: b= -0.199, F(1,112) = 1.263 [t(112) = -1.124], p = 0.264, for interest to use AM: b= -0.224, F(1,112) = 1.663 [t(112) = -1.29], p = 0.2, for motivation to learn AM: b= -0.286, F(1,112) = 2.561 [t(112) = -1.6], p = 0.112, for motivation to use AM: b= -0.181, F(1,112) = 0.886 [t(112) = -0.942], p = 0.348). Many participants generally agreed or strongly agreed (Fig. 3a) that they were interested and motivated to learn about and use AM within each condition.

Regressing the distributions of the prior awareness in AM, ME, and DfME on the centered condition (CAE= -0.5, VR= 0, REAL= 0.5) showed no observable significant difference between the three conditions in prior awareness (for AM: b= -0.194, F(1,112) = 1.237 [t(112) = -1.112], p = 0.268, for ME: b= -0.114, F(1,112) = 0.291 [t(112) = -0.54], p = 0.591, for DfME: b= -0.302, F(1,112) = 2.215 [t(112) = -1.488], p = 0.139). As shown in Fig. 3b, the distribution of awareness in AM, ME, and DfME suggests that the collective experience within the three conditions was similar; however, while many participants had some form of informal or formal experience with AM, ME, and DfME, participants claimed a significantly higher awareness of general AM than they did specifically of ME (b= 6.667, F(2,6) = 10.42 [t(6) = 3.651], p = 0.01) and DfME (b= 7.667, F(2,6) = 10.422 [t(6) = 4.199], p = 0.006). This can be observed in Fig. 3b with the significantly higher number of participants reporting that they had "never heard or learnt about" ME or DfME before the study indicating that they were novices to ME. These analyses suggest that the results from later design evaluations can be attributed to changes in the experimental factors, rather than underlying variations in interest, motivation, or prior awareness.

Lastly, regressing the collapsed technology comfort levels on the centered condition (CAE= -0.5, VR= 0.5) showed that participants in the CAE condition had a significantly higher comfort for CAE technology than did participants in the VR condition for VR technology (b= -0.749, F(1,77) = 11.79 [t(77) = -3.434], p < 0.001). This result was expected as this research worked with second to third-year undergraduate students from an engineering design methodology course at an R1 university who would have completed at least one semester of CAE course requirements, and likely not have completed any VR course work. Nonetheless, the analysis suggests that effects from varying comfort levels for the technologies in each condition could influence the study, however, with the limited scope in mind for this work, we acknowledge the limitation of not accounting for technology comfort levels that will be considered as an opportunity for future work.

5.2 Design evaluation as affected by the conditions

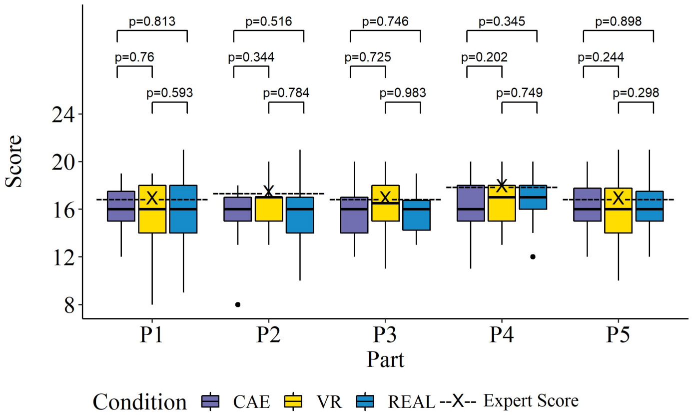
For the first research question, this research aimed to understand how the differences in evaluation conditions (i.e., CAE, VR, REAL) affected the results of the design evaluation as measured by the DfAM score, evaluation time, and confidence of evaluation. Figure 4 highlights the results of the evaluation for each design across each condition. We hypothesized that design DfAM scores, time taken for the evaluation, and confidence in evaluation between the conditions will differ as the designs change. To study this, the DfAM score, evaluation time, and reported confidence were regressed on the centered variables for condition (CAE = -0.5, VR = 0, REAL = 0.5; between-subjects variable) and design (D1 = -0.5, D2= -0.25, D3 = 0, D4 = 0.25, D5 = 0.5; within-subjects variable) as the covariate. The analysis utilized restricted maximum likelihood estimation to iteratively modify the parameter estimates to minimize the log-likelihood function and evaluated this model with the Kenward and Rogers (KR) adjustment [63]. The following results reported from the analysis focus on each detailed effect when controlling for all other main effects in the model. No interaction effects between any of the independent variables were considered in the analysis.

The main analysis showed no significant effect of condition on score (b = 0.312, F(1,112) = 0.553 [t(112) = 0.744], p = 0.458), time (b = -24.653, F(1,112) = x [t(112) = -1.276], p = 0.204), or confidence (b = -0.223, F(1,112) = 0.287 [t(112) = -0.535], p = 0.593). As can be observed from Fig. 4, this analysis suggests that participants generally did not display a significant difference between the conditions when evaluating different designs and generally reported identical scores, experienced identical times, and were equally confident across the mediums. The main analysis also showed no significant effect of design on score (b = 0.4, F(1,112) = 1.634 [t(112) = 1.278], p = 0.204), time (b = 13.657, F(1,112) = 0.374 [t(112) = 0.611], p = 0.542), and confidence (b = -0.272, F(1,112) = 1.953 [t(112) = -1.397], p = 0.1662). This further suggests that participants generally did not identify any significant differences between the designs themselves in regard to their DfAM scores, the time it takes to evaluate the designs, and the confidence for evaluating the designs.

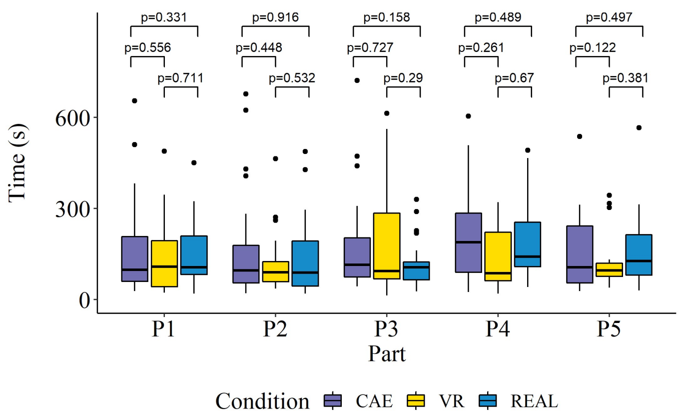
To identify whether novices scored the parts similarly to experts, the DfAM score (collapsed expert and novice scores) was regressed on the centered variables for expertise (Novice = -0.5, Expert = 0.5; between-subjects variable) and design (D1 = -0.5, D2= -0.25, D3 = 0, D4 = 0.25, D5 = 0.5; within-subjects variable) as the covariate. The expert scores were calculated after confirming the inter-rater agreement between two experts using a weighted Kohen's kappa (κ) with linear weights. The agreement was calculated from the individual scores for each metric in the worksheet and not the cumulative scores. The calculated κ value of 0.739 was considered to represent good to an excellent agreement beyond chance. The averages of the expert scores were taken and summed to obtain the total DfAM scores for each design. As can be observed in Fig. 4b, the regression analysis of collapsed DfAM score on expertise and design showed no significant effect of design on the DfAM score (b = 0.386, F(1,7) = 1.269 [t(7) = 1.127], p = 0.297) and no significant difference between the expert and novice scores (b = 1.253, F(1,7) = 4.108 [t(7) = 2.027], p = 0.823). This suggests that like the novices, the experts also did not identify any significant differences between the designs themselves concerning their DfAM scoring. This observation of expert scoring indicates a potential issue with the chosen geometries for this research suggesting that the preliminary condition of the designs having sufficiently varying manufacturability needs to be reassessed (elaborated upon in Section 6, RQ1).

5.3 Cognitive load as affected by the conditions

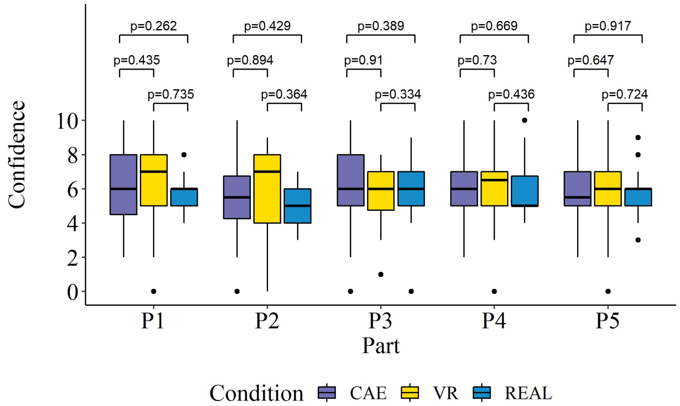
For the second research question, this research aimed to understand how the differences in evaluation conditions (i.e., CAE, VR, REAL) affected the cognitive load experienced from the evaluation exercise as measured by the eight dimensions in the WPA



(a) DfAM score as affected by the three conditions compared to a condition-independent expert score for each design



(b) Time taken by participants to evaluate each design as affected by the three conditions



(c) Confidence in the DfAM evaluation for each design as affected by the three conditions

FIGURE 4: Highlighting the results from the DfAM evaluation for each design as affected by the three conditions

tool. Figure 5 highlights the cognitive load experienced across each condition. We hypothesized that cognitive load between the conditions will differ as the characteristics of the medium and the tasks and required motor skills needed to adequately evaluate the designs change. To study this, cognitive load was regressed on the centered variable for condition (CAE = -0.5, VR = 0, REAL = 0.5; between-subjects variable) using a multiple regression model which regressed the grouped cognitive load values. The following results reported from the analysis focus on each detailed effect when controlling for all other main effects in the model.

The main analysis showed no statistically significant difference in cognitive load for any of the WPA dimensions across the three conditions (Table. 3). As can be observed from Fig. 5, this analysis suggests that participants generally did not experience one medium to require more or less mental effort than the others when completing the design evaluation exercise.

TABLE 3: List of the different cognitive load dimensions indicating how they generally differ across the conditions

Dimension	Estimate	SE	t.ratio	p.value
Auditory	-0.35	0.667	-0.52	0.597
Manual	1.17	0.611	1.92	0.056
Perceptual	0.05	0.431	0.13	0.896
Response	-0.51	0.504	-1.02	0.308
Spatial	-0.33	0.507	-0.65	0.513
Speech	0.03	0.661	0.04	0.963
Verbal	-0.63	0.652	-0.96	0.334
Visual	0.39	0.535	0.74	0.459

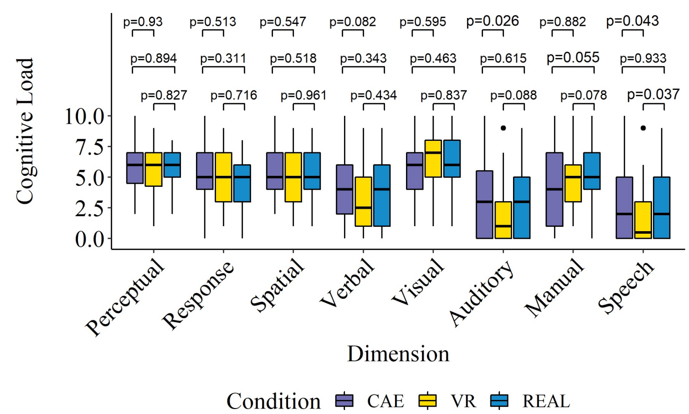


FIGURE 5: Showcasing the distribution of reported cognitive load as affected by the three conditions

While the analysis indicates that there was generally no significant difference in cognitive load between the conditions, Table. 3 and Fig. 5 suggest that there was an emerging trend observed for the manual cognitive load dimension seemingly driven by the REAL condition. However, the sample size of the current dataset is insufficient to infer more information for potentially significant trends (elaborated upon in Section 6, RQ2).

6. DISCUSSION

This work found that novice designers do not experience significant differences in their DfAM evaluation of designs for manufacturability by ME. They also do not experience significant differences in their mental effort to evaluate the designs when using mediums of different immersion. Additionally, both novices and experts did not perceive significant differences in manufacturability between the five different designs presented (Fig. 2) as indicated by their DfAM scoring. These findings present interesting implications for DfAM and product development when leveraging immersive or non-immersive mediums of evaluation and indicate key avenues for future research opportunities to further expand AM and DfAM knowledge in literature. This section thus highlights the implications of our collective findings on the proposed research questions and elaborates on the interpretation behind the observed results and their underlying mechanisms.

RQ1: How do the differences in immersion between CAE, VR, and REAL mediums affect the DfAM evaluation results for designs of varying manufacturability?

For the first research question, this research aimed to understand how differences in immersion between mediums of evaluation affect the DfAM evaluation of designs. We hypothesized that the evaluation through VR and REAL conditions would yield scores significantly closer to expert-reviewed scores, faster evaluation times, and higher reported confidence values than evaluation through the CAE condition, but with no significant differences between the two immersive conditions. The results and analysis in section 5.2 failed to reject the null hypothesis for each metric (i.e., score, time, confidence) which indicates that this study did not identify any generally significant effects from immersion on the results of the design evaluation. However, in addition to not identifying any significant effects from immersion on the results of the design evaluation, this study also did not identify any significant differences in design DfAM scoring between the five designs when controlling for the condition. This suggests that our findings for research question 1 are influenced by the limited design variation (as measured by manufacturability) among the designs used in this study. A posthoc observation of the data was conducted to further evaluate this influence and understand whether the variation in the designs was limited in this research.

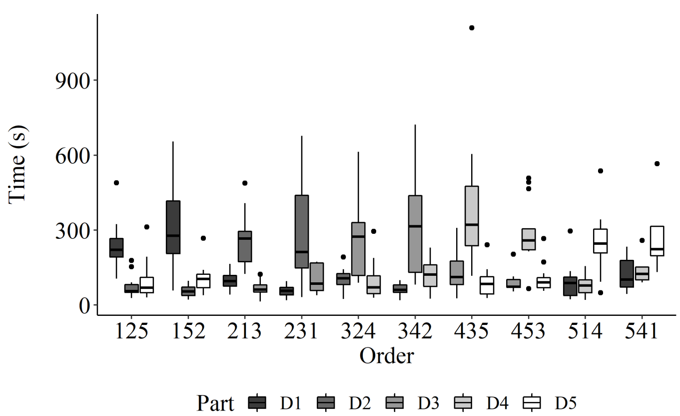


FIGURE 6: Showcasing the distribution of time taken to evaluate designs with respect to the ordered set of evaluation (e.g., set 125 indicates that participants evaluated D1, D2, and D5 in order)

The distribution of the time taken for each design evaluation as shown in Fig. 6 indicates that participants generally spent more time on the first design they evaluated but spent less time for the following two designs. This can be observed for all the ordered sets, suggesting that participants displayed this trend regardless of which design they saw first and which designs were included in their ordered set. The duration of the second and third analyses was less than the duration of the first evaluation and participants also spent roughly identical time intervals for the second and third analyses. This trend where time taken between the first and the two following analyses is a strong indicator that participants found the three designs identical regarding manufacturability by ME because the differences in manufacturability between the three designs were trivial. Furthermore, this influence on the participant experiences by the limited diversity in manufacturability of the designs is suggestive of why both novices and experts did not report significantly different DfAM scores for the different designs. Regarding the goals for research question 1, these observations imply that immersion does not play an observable role in design evaluation when designers are given designs that do not vary significantly in manufacturability even though they may vary in design complexity. This is observed in Fig. 4b which shows that there is no significant difference in DfAM scores between any of the five designs regardless of the condition. Findings from past work suggest that limited variations in complexity may not be reflected in product or design evaluation [51]. The observations in this research due to the limited variations in manufacturability may extend to these past observations due to the limited variations in complexity. Therefore, the variation in complexity and manufacturability of the designs needs to be larger for designers to assess the manufacturability of the designs differently.

RQ2: How do the differences in immersion between CAE, VR, and REAL mediums affect the cognitive load experienced when evaluating designs of varying manufacturability?

For the second research question, this research aimed to understand how differences in immersion affect the cognitive load experienced from a design evaluation exercise. We hypothesized that the VR and REAL experiences would require significantly less mental effort and yield lower reported cognitive load values than the CAE experience, but with no significant differences between the two immersive conditions. The results and analysis in section 5.3 failed to reject the null hypothesis for each cognitive load dimension which indicates that this study did not identify any generally significant differences in mental effort due to immersion. This means that designers may generally find using immersive or non-immersive mediums equally challenging when evaluating their product designs for manufacturability with ME. These findings are based on the inferred low difficulty of the given task. Evaluating designs for manufacturability may likely be similar to past research into low difficulty operations [51, 53, 55], our findings indicate that designers do not experience requiring significantly different mental effort when working with immersive and non-immersive media for DfAM evaluation tasks. Specifically, the low manual and processing difficulty required by the task of evaluating designs for manufacturability with ME likely contributed to the observed experiential similarities between the three mediums. The low difficulty can be attributed to the relative simplicity and small scale of the five designs that were evaluated.

When considering more complex designs and manufacturability considerations, such as those involving lattice or generative design features, designers may experience a higher cognitive load as the difficulty of processing information and manually assessing manufacturability within the medium increases [51, 52, 54, 56].

7. CONCLUSION

The goal of this research was to identify the effects of immersion in the design experience and study how evaluating designs for DfAM in mediums of varying immersion affects the results of the evaluation and the mental effort experienced to evaluate the designs. This research measured the DfAM score, time taken for evaluation, and confidence in the evaluation to study the DfAM results from the experience and measured cognitive load using the WPA tool to study the mental effort experienced to evaluate designs from the experience. The results in section 5 indicate that differences in immersion between the three mediums (CAE, VR, and REAL) did not significantly affect the manufacturability evaluation of any of the five designs. Immersion also did not impact the cognitive load experienced by the participants from their DfAM exercises. These findings suggest that designers can use immersive and non-immersive mediums for design evaluation without experiencing significant differences in their evaluation outcomes and mental effort. This implies that industries can tailor their product and designer-talent development initiatives by using modular design evaluation systems that leverage capabilities in both immersive and non-immersive DfAM evaluation.

While the results in section 5 highlight the similarity of the three mediums (CAE, VR, REAL) in the design evaluation and cognitive load when evaluating designs for manufacturability by ME, these findings need to be considered with certain limitations of this work. This research limited its scope toward manufacturability evaluation for ME. Material extrusion is a relatively more accessible and functionally less complex process than processes like powder bed fusion. Therefore, the findings from this work are limited to manufacturability evaluations when the AM process is functionally simpler and the relevant DfAM considerations of the process are in turn easier to evaluate. However, knowledge from future work will expand on ongoing work [12] that explores learning and intuition development for multiple AM processes. Doing so will aid industries in improving their digital threads by empowering their designers to meet AM-driven product design needs for a range of AM processes. Additionally, this work identified underlying trends and observations from the data that did not answer aspects of the studied research questions. Specifically, this research identified the lack of diversity in manufacturability between the five designs evaluated by the designers and concluded that the insufficient variation between the designs could not sufficiently highlight how the differences in immersion affect the DfAM evaluation and the experienced cognitive load when designers evaluate designs of varying manufacturability. However, knowledge from future work will address this limitation in inadequate design diversity by using validated process-agnostic tools to identify expert reviewed designs of low and high complexity. Such work will enhance our current findings and will further inform industries on how to train their designers to assess product needs that require evaluating widely complex designs and their manufacturing requirements.

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REFERENCES

[1] Wohlers, T. T., Campbell, I., Diegel, O., Huff, R. and Kowen, J. "Wohlers Report 2021: 3D Printing and Additive Manufacturing Global State of the Industry." *Wohlers Associates, Fort Collins, CO, USA* .

[2] Roberts, Tess and Bartkova, Barbara. "Additive Manufacturing Trend Report." Technical Report No. 2021. Hubs Inc., Amsterdam, The Netherlands. 2021.

[3] Jiang, Ruth, Kleer, Robin and Piller, Frank T. "Predicting the Future of Additive Manufacturing: A Delphi Study on Economic and Societal Implications of 3D Printing for 2030." *Technological Forecasting and Social Change* Vol. 117 (2017): pp. 84–97. DOI 10.1016/j.techfore.2017.01.006.

[4] Ford, Simon and Despeisse, Mélanie. "Additive Manufacturing and Sustainability: An Exploratory Study of the Advantages and Challenges." *Journal of Cleaner Production* Vol. 137 (2016): pp. 1573–1587. DOI 10.1016/j.jclepro.2016.04.150.

[5] Huang, Yong and Leu, Ming C. "Frontiers of Additive Manufacturing Research and Education." .

[6] Thomas-Seale, L.E.J., Kirkman-Brown, J.C., Attallah, M.M., Espino, D.M. and Shepherd, D.E.T. "The Barriers to the Progression of Additive Manufacture: Perspectives from UK Industry." *International Journal of Production Economics* Vol. 198 (2018): pp. 104–118. DOI 10.1016/j.ijpe.2018.02.003.

[7] Meisel, Nicholas and Williams, Christopher. "An Investigation of Key Design for Additive Manufacturing Constraints in Multimaterial Three-Dimensional Printing." *ASME Journal of Mechanical Design* Vol. 137 No. 11 (2015): p. 111406. DOI 10.1115/1.4030991.

[8] Thompson, Mary Kathryn, Moroni, Giovanni, Vaneker, Tom, Fadel, Georges, Campbell, R. Ian, Gibson, Ian, Bernard, Alain, Schulz, Joachim, Graf, Patricia, Ahuja, Bhrigu and Martina, Filomeno. "Design for Additive Manufacturing: Trends, Opportunities, Considerations, and Constraints." *CIRP Annals* Vol. 65 No. 2 (2016): pp. 737–760. DOI 10.1016/j.cirp.2016.05.004.

[9] Booth, Joran W., Alperovich, Jeffrey, Chawla, Pratik, Ma, Jiayan, Reid, Tahira N. and Ramani, Karthik. "The Design for Additive Manufacturing Worksheet." *ASME Journal of Mechanical Design* Vol. 139 No. 10 (2017): p. 100904. DOI 10.1115/1.4037251.

[10] Kumke, Martin, Watschke, Hagen, Hartogh, Peter, Bavendiek, Ann-Kathrin and Vietor, Thomas. "Methods

and Tools for Identifying and Leveraging Additive Manufacturing Design Potentials." *International Journal on Interactive Design and Manufacturing (IJIDeM)* Vol. 12 No. 2 (2018): pp. 481–493. DOI 10.1007/s12008-017-0399-7.

[11] Blösch-Paidosh, Alexandra and Shea, Kristina. "Design Heuristics for Additive Manufacturing Validated Through a User Study1." *ASME Journal of Mechanical Design* Vol. 141 No. 4 (2019): p. 041101. DOI 10.1115/1.4041051.

[12] Mathur, Jayant, Miller, Scarlett R., Simpson, Timothy W. and Meisel, Nicholas A. "Analysis of the Knowledge Gain and Cognitive Load Experienced Due to the Computer-Aided Instruction of Additive Manufacturing Processes." *Proceedings of the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 4: 18th International Conference on Design Education (DEC)*. DETC2021-71667: p. V004T04A013. Virtual, Online, August 17, 2021. DOI 10.1115/DETC2021-71667.

[13] Simpson, Timothy W., Williams, Christopher B. and Hripko, Michael. "Preparing Industry for Additive Manufacturing and Its Applications: Summary & Recommendations from a National Science Foundation Workshop." *Additive Manufacturing* Vol. 13 (2017): pp. 166–178. DOI 10.1016/j.addma.2016.08.002.

[14] Prabhu, Rohan, Bracken, Jennifer, Armstrong, Clinton B., Jablokow, Kathryn, Simpson, Timothy W. and Meisel, Nicholas A. "Additive Creativity: Investigating the Use of Design for Additive Manufacturing to Encourage Creativity in the Engineering Design Industry." *International Journal of Design Creativity and Innovation* Vol. 8 No. 4 (2020): pp. 198–222. DOI 10.1080/21650349.2020.1813633.

[15] Bracken, Jennifer, Pomorski, Thomas, Armstrong, Clinton, Prabhu, Rohan, Simpson, Timothy W., Jablokow, Kathryn, Cleary, William and Meisel, Nicholas A. "Design for Metal Powder Bed Fusion: The Geometry for Additive Part Selection (GAPS) Worksheet." *Additive Manufacturing* Vol. 35 (2020): p. 101163. DOI 10.1016/j.addma.2020.101163.

[16] Lauff, Carlye A., Perez, K. Blake, Camburn, Bradley A. and Wood, Kristin L. "Design Principle Cards: Toolset to Support Innovations With Additive Manufacturing." *Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 4: 24th Design for Manufacturing and the Life Cycle Conference; 13th International Conference on Micro- and Nanosystems*. DETC2019-97231: p. V004T05A005. Anaheim, California, USA, August 18, 2019. DOI 10.1115/DETC2019-97231.

[17] Buxton, William. *Sketching User Experiences: Getting the Design Right and the Right Design*. Elsevier/Morgan Kaufmann, Amsterdam Boston (2007).

[18] Ibrahim, Rahinah and Pour Rahimian, Farzad. "Comparison of CAD and Manual Sketching Tools for Teaching Architectural Design." *Automation in Construction* Vol. 19 No. 8 (2010): pp. 978–987. DOI 10.1016/j.autcon.2010.09.003.

[19] Feeman, Seth M., Wright, Landon B. and Salmon, John L. "Exploration and Evaluation of CAD Modeling in Virtual Reality." *Taylor & Francis Computer-Aided Design and Applications* Vol. 15 No. 6 (2018): pp. 892–904. DOI 10.1080/16864360.2018.1462570.

[20] Wolfartsberger, Josef. "Analyzing the Potential of Virtual Reality for Engineering Design Review." *Automation in Construction* Vol. 104 (2019): pp. 27–37. DOI 10.1016/j.autcon.2019.03.018.

[21] Barnawal, Prashant, Dorneich, Michael C., Frank, Matthew C. and Peters, Frank. "Evaluation of Design Feedback Modality in Design for Manufacturability." *ASME Journal of Mechanical Design* Vol. 139 No. 9 (2017): p. 094503. DOI 10.1115/1.4037109.

[22] Horvat, Nikola, Škec, Stanko, Martinec, Tomislav, Lukačević, Fanika and Perišić, Marija Majda. "Comparing Virtual Reality and Desktop Interface for Reviewing 3D CAD Models." *Proceedings of the Design Society: International Conference on Engineering Design* Vol. 1 No. 1 (2019): pp. 1923–1932. DOI 10.1017/dsi.2019.198.

[23] Guo, Ziyue, Zhou, Dong, Chen, Jiayu, Geng, Jie, Lv, Chuan and Zeng, Shengkui. "Using Virtual Reality to Support the Product's Maintainability Design: Immersive Maintainability Verification and Evaluation System." *Computers in Industry* Vol. 101 (2018): pp. 41–50. DOI 10.1016/j.compind.2018.06.007.

[24] Abidi, Mustufa Haider, Al-Ahmari, Abdulrahman, Ahmad, Ali, Ameen, Wadea and Alkhalefah, Hisham. "Assessment of Virtual Reality-Based Manufacturing Assembly Training System." *The International Journal of Advanced Manufacturing Technology* Vol. 105 No. 9 (2019): pp. 3743–3759. DOI 10.1007/s00170-019-03801-3.

[25] Bharathi, Ajay Karthic B. Gopinath and Tucker, Conrad S. "Investigating the Impact of Interactive Immersive Virtual Reality Environments in Enhancing Task Performance in Online Engineering Design Activities." *Proceedings of the ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 3: 17th International Conference on Advanced Vehicle Technologies; 12th International Conference on Design Education; 8th Frontiers in Biomedical Devices*. DETC2015-47388: p. V003T04A004. Boston, Massachusetts, USA, August 2, 2015. DOI 10.1115/DETC2015-47388.

[26] Ostrander, John K., Ryan, Lauren, Dhengre, Snehal, McComb, Christopher, Simpson, Timothy W. and Meisel, Nicholas A. "A Comparative Study of Virtual Reality and Computer-Aided Design to Evaluate Parts for Additive Manufacturing." *Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 2A: 45th Design Automation Conference*. DETC2019-97480: p. V02AT03A029. Anaheim, California, USA, August 18, 2019. DOI 10.1115/DETC2019-97480.

[27] Radianti, Jaziar, Majchrzak, Tim A., Fromm, Jennifer and Wohlgenannt, Isabell. "A Systematic Review of Immersive Virtual Reality Applications for Higher Education: Design Elements, Lessons Learned, and Research Agenda." *Computers & Education* Vol. 147 (2020): p. 103778. DOI 10.1016/j.compedu.2019.103778.

[28] Slater, Mel and Wilbur, Sylvia. "A Framework for Immersive Virtual Environments (FIVE): Speculations on the Role of Presence in Virtual Environments." *Presence: Teleoperators and Virtual Environments* Vol. 6 No. 6 (1997): pp. 603–616. DOI 10.1162/pres.1997.6.6.603.

[29] Jensen, Lasse and Konradsen, Flemming. "A Review of the Use of Virtual Reality Head-Mounted Displays in Education and Training." *Education and Information Technologies* Vol. 23 No. 4 (2018): pp. 1515–1529. DOI 10.1007/s10639-017-9676-0.

[30] Freina, Laura and Ott, Michela. "A Literature Review on Immersive Virtual Reality in Education: State of the Art and Perspectives." *The International Scientific Conference Elearning and Software for Education*: pp. 10–1007.

[31] Boschma, Ron. "Proximity and Innovation: A Critical Assessment." *Regional Studies* Vol. 39 No. 1 (2005): pp. 61–74. DOI 10.1080/0034340052000320887.

[32] Gibson, Ian, Rosen, David, Stucker, Brent and Khorasani, Mahyar. *Additive Manufacturing Technologies*. Springer International Publishing, Cham (2021). DOI 10.1007/978-3-030-56127-7.

[33] Shi, Yang, Zhang, Yicha, Baek, Steven, De Backer, Wout and Harik, Ramy. "Manufacturability Analysis for Additive Manufacturing Using a Novel Feature Recognition Technique." *Computer-Aided Design and Applications* Vol. 15 No. 6 (2018): pp. 941–952. DOI 10.1080/16864360.2018.1462574.

[34] Ranjan, Rajit, Samant, Rutuja and Anand, Sam. "Design for Manufacturability in Additive Manufacturing Using a Graph Based Approach." *Proceedings of the ASME 2015 International Manufacturing Science and Engineering Conference*, *Volume 1: Processing*. MSEC2015-9448: p. V001T02A069. Charlotte, North Carolina, USA, June 8, 2015. DOI 10.1115/MSEC2015-9448.

[35] Tedia, Saish and Williams, Christopher B. "Manufacturability Analysis Tool for Additive Manufacturing Using Voxel-Based Geometric Modeling." *27th Annual International Solid Freeform Fabrication (SFF) Symposium*: pp. 3–22.

[36] Caviggioli, Federico and Ughetto, Elisa. "A Bibliometric Analysis of the Research Dealing with the Impact of Additive Manufacturing on Industry, Business and Society." *International Journal of Production Economics* Vol. 208 (2019): pp. 254–268. DOI 10.1016/j.ijpe.2018.11.022.

[37] Noh, Heena, Park, Kijung, Park, Kiwon and Okudan Kremer, Gül E. "Development of a Design for Additive Manufacturing Worksheet for Medical Casts." *Proceedings of the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 5: 26th Design for Manufacturing and the Life Cycle Conference (DFMLC)*. DETC2021-72103: p. V005T05A004. Virtual, Online, August 17, 2021. DOI 10.1115/DETC2021-72103.

[38] Gross, Jared, Park, Kijung and Kremer, Gül E. Okudan. "Design for Additive Manufacturing Inspired by TRIZ." *Proceedings of the ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *Volume 4: 23rd Design for Manufacturing and the Life Cycle Conference; 12th International Conference on Micro- and Nanosystems*. DETC2018-85761: p. V004T05A004. Quebec City, Quebec, Canada, August 26, 2018. DOI 10.1115/DETC2018-85761.

[39] Chirico Scheele, Stefania, Binks, Martin and Egan, Paul F. "Design and Manufacturing of 3D Printed Foods With User Validation." *Proceedings of the ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, *ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. DETC2020-22462: p. V006T06A003, November 3, 2020. DOI 10.1115/DETC2020-22462.

[40] Budinoff, Hannah D. and McMains, Sara. "Will It Print: A Manufacturability Toolbox for 3D Printing." *International Journal on Interactive Design and Manufacturing (IJIDeM)* Vol. 15 No. 4 (2021): pp. 613–630. DOI 10.1007/s12008-021-00786-w.

[41] Fillingim, Kenton Blane, Nwaeri, Richard O., Paredis, Christiaan J. J., Rosen, David and Fu, Katherine. "Examining the Effect of Design for Additive Manufacturing Rule Presentation on Part Redesign Quality." *Journal of Engineering Design* Vol. 31 No. 8-9 (2020): pp. 427–460. DOI 10.1080/09544828.2020.1789569.

[42] Camburn, Bradley, Dunlap, Brock, Gurjar, Tanmay, Hamon, Christopher, Green, Matthew, Jensen, Daniel, Crawford, Richard, Otto, Kevin and Wood, Kristin. "A Systematic Method for Design Prototyping." *ASME Journal of Mechanical Design* Vol. 137 No. 8 (2015): p. 081102. DOI 10.1115/1.4030331.

[43] Viswanathan, Vimal K. and Linsey, Julie S. "Physical Models and Design Thinking: A Study of Functionality, Novelty and Variety of Ideas." *ASME Journal of Mechanical Design* Vol. 134 No. 9 (2012): p. 091004. DOI 10.1115/1.4007148.

[44] Gibson, Ian, Gao, Zhan and Campbell, Ian. "A Comparative Study of Virtual Prototyping and Physical Prototyping." *International Journal of Manufacturing Technology and Management* Vol. 6 No. 6 (2004): p. 503. DOI 10.1504/IJMTM.2004.005931.

[45] Zorriassatine, F, Wykes, C, Parkin, R and Gindy, N. "A Survey of Virtual Prototyping Techniques for Mechanical Product Development." *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* Vol. 217 No. 4 (2003): pp. 513–530. DOI 10.1243/095440503321628189.

[46] Lynn, Roby, Saldana, Christopher, Kurfess, Thomas, Reddy, Nithin, Simpson, Timothy, Jablokow, Kathryn, Tucker, Tommy, Tedia, Saish and Williams, Christopher. "Toward Rapid Manufacturability Analysis Tools for Engineering Design Education." *Procedia Manufacturing* Vol. 5 (2016): pp. 1183–1196. DOI 10.1016/j.promfg.2016.08.093.

[47] de Jong, Ton, Linn, Marcia C. and Zacharia, Zacharias C. "Physical and Virtual Laboratories in Science and Engineering Education." *Science* Vol. 340 No. 6130 (2013): pp. 305–308. DOI 10.1126/science.1230579.

[48] Ouyang, Shu-Guang, Wang, Gang, Yao, Jun-Yan, Zhu, Guang-Heng-Wei, Liu, Zhao-Yue and Feng, Chi. "A Unity3D-based Interactive Three-Dimensional Virtual Practice Platform for Chemical Engineering." *Computer Applications in Engineering Education* Vol. 26 No. 1 (2018): pp. 91–100. DOI 10.1002/cae.21863.

[49] Berg, Leif P. and Vance, Judy M. "Industry Use of Virtual Reality in Product Design and Manufacturing: A Survey." *Virtual Reality* Vol. 21 No. 1 (2017): pp. 1–17. DOI 10.1007/s10055-016-0293-9.

[50] Vergara, Diego, Fernández-Arias, Pablo, Extremera, Jamil, Dávila, Lilian P. and Rubio, Manuel P. "Educational Trends Post COVID-19 in Engineering: Virtual Laboratories." *Materials Today: Proceedings* Vol. 49 (2022): pp. 155–160. DOI 10.1016/j.matpr.2021.07.494.

[51] Starkey, Elizabeth M., McKay, Alexander S., Hunter, Samuel T. and Miller, Scarlett R. "Piecing Together Product Dissection: How Dissection Conditions Impact Student Conceptual Understanding and Cognitive Load." *ASME Journal of Mechanical Design* Vol. 140 No. 5 (2018): p. 052001. DOI 10.1115/1.4039384.

[52] Pontonnier, Charles, Dumont, Georges, Samani, Asfhin, Madeleine, Pascal and Badawi, Marwan. "Designing and Evaluating a Workstation in Real and Virtual Environment: Toward Virtual Reality Based Ergonomic Design Sessions." *Journal on Multimodal User Interfaces* Vol. 8 No. 2 (2014): pp. 199–208. DOI 10.1007/s12193-013-0138-8.

[53] Wismer, Andrew, Reinerman-Jones, Lauren, Teo, Grace, Willis, Sasha, McCracken, Kelsey and Hackett, Matthew. "A Workload Comparison During Anatomical Training with a Physical or Virtual Model." *Augmented Cognition: Users and Contexts*. Vol. 10916. Springer International Publishing, Cham (2018): pp. 240–252.

[54] Makransky, Guido, Terkildsen, Thomas S. and Mayer, Richard E. "Adding Immersive Virtual Reality to a Science Lab Simulation Causes More Presence but Less Learning." *Learning and Instruction* Vol. 60 (2019): pp. 225–236. DOI 10.1016/j.learninstruc.2017.12.007.

[55] Armougum, A., Orriols, E., Gaston-Bellegarde, A., Marle, C. Joie-La and Piolino, P. "Virtual Reality: A New Method to Investigate Cognitive Load during Navigation." *Journal of Environmental Psychology* Vol. 65 (2019): p. 101338. DOI 10.1016/j.jenvp.2019.101338.

[56] Frederiksen, Joakim Grant, Sørensen, Stine Maya Dreier, Konge, Lars, Svendsen, Morten Bo Søndergaard, Nobel-Jørgensen, Morten, Bjerrum, Flemming and Andersen, Steven Arild Wuyts. "Cognitive Load and Performance in Immersive Virtual Reality versus Conventional Virtual Reality Simulation Training of Laparoscopic Surgery: A Randomized Trial." *Surgical Endoscopy* Vol. 34 No. 3 (2020): pp. 1244–1252. DOI 10.1007/s00464-019-06887-8.

[57] Mathur, Jayant. "DfAM Worksheet." Version 1. Made by Design Lab (2022). https://sites.psu.edu/madebydesign/files/2017/07/worksheet.pdf.

[58] Bradley, James V. "Complete Counterbalancing of Immediate Sequential Effects in a Latin Square Design." *[American Statistical Association, Taylor & Francis, Ltd.] Journal of the American Statistical Association* Vol. 53 No. 282 (1958): pp. 525–528. DOI 10.2307/2281872.

[59] Tsang, Pamela S. and Velazquez, Velma L. "Diagnosticity and Multidimensional Subjective Workload Ratings." *Ergonomics* Vol. 39 No. 3 (1996): pp. 358–381. DOI 10.1080/00140139608964470.

[60] Rubio, Susana, Diaz, Eva, Martin, Jesus and Puente, Jose M. "Evaluation of Subjective Mental Workload: A Comparison of SWAT, NASA-TLX, and Workload Profile Methods." *Applied Psychology* Vol. 53 No. 1 (2004): pp. 61–86. DOI 10.1111/j.1464-0597.2004.00161.x.

[61] Peña, Edsel A and Slate, Elizabeth H. "Global Validation of Linear Model Assumptions." *Journal of the American Statistical Association* Vol. 101 No. 473 (2006): pp. 341–354. DOI 10.1198/016214505000000637.

[62] Loy, Adam and Hofmann, Heike. "HLMdiag : A Suite of Diagnostics for Hierarchical Linear Models in R." *Journal of Statistical Software* Vol. 56 No. 5. DOI 10.18637/jss.v056.i05.

[63] Kenward, Michael G. and Roger, James H. "Small Sample Inference for Fixed Effects from Restricted Maximum Likelihood." *Biometrics* Vol. 53 No. 3 (1997): p. 983. DOI 10.2307/2533558.