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Improving the Student Makerspace Experience by Using Crowdsourcing to Identify Common Build Failure*

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The maker movement has led to an increase in university makerspaces, where a low barrier-to-entry enables students of all experience levels to engage with technology such as additive manufacturing (AM). However, the range of student skills can result in frequent build failures, which in turn contribute to increased maintenance or student frustration. To identify key causes behind failed AM builds in a student-focused makerspace, this paper outlines how a crowdsourcing-based data collection tool was formulated that automatically extracts design and print information through printer files and correlates this information with student evaluations of their part's build quality, thus allowing for common sources of failure within the space to be readily identified. 77 unique makerspace builds, made up of 228 individual parts, were collected and analyzed for relationships between build quality and parameters selected in the slicing process. Through this approach, student-focused makerspaces may be able to leverage the significant amount of design and manufacturing information being processed through the space to better support student efforts, thus reducing the potential for frustration and improve learning outcomes.

Keywords: crowdsourcing; additive manufacturing; informal learning; makerspaces

1. Introduction

The rise of the maker movement, a recent culture inviting many to use a wide range of equipment to suit their creative wants, has led to the increased availability of open-access makerspaces. Makerspaces offer a location where communities of practice can come together to work with various pieces of potentially costly equipment at a low barrier to entry. Areas commonly found in makerspaces include woodshops, metal shops, textile labs, and additive manufacturing (AM) labs, enabling students to take part in creating any number of projects. AM, the process of creating a desired object or assembly by layering material together in a constructed pattern aided by a 3D model, is especially common in makerspaces due to its low machine and material costs. AM machines can reduce material waste compared with traditional manufacturing processes and offer many benefits such as enabling geometries that are difficult or impossible to machine while being safe for general use in an open access space [1].

The inclusive nature of a makerspace is evident by the philosophy of welcoming individuals regardless of their past experience and helping them to create [2, 3]. After an initial training, it is common practice for newcomers to advance their understanding of the different technologies, such as AM, simply through trial and error [4, 5]. As an example, students with minimal AM experience may download a 3D model from the internet, prepare the files in slicing software and immediately try to produce the part. However, if improper settings are selected, the fabrication may fail, requiring novice students to return to the settings to begin learning the necessary metrics involved with a successful AM tray [6]. When the machine is calibrated correctly and the student is knowledgeable in AM, the manufacturing process can become more successful; however, novice makerspace students will likely see many failures when first using AM technology. Material Extrusion (MEX) machines [7] are the most common type of AM technology found in makerspaces, due to their low cost, risk, and time to generate the desired object [8, 9]; however, by being available to novices, there is the potential for a more frequent maintenance schedule. While MEX machines can malfunction through regular use, they can also break as a result of a failure during the printing process. For example, a poorly prepared tray can cause material to flood the extruder which can lead to a clogged nozzle and encourage future builds to fail.

In an open-access makerspace where students are novices to AM, frequent failures and increased machine maintenance are likely. As such, makerspaces would benefit from a validated resource to

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support student users that helps to predict whether a prepared MEX tray has a high probability of failure. An opportunity exists to crowdsource vast amounts of AM data to determine which aspects of the printing process largely affect the success of a novice tray within a given makerspace. This paper introduces and details the deployment of a crowdsourcing-based survey tool that has a makerspace's students upload their sliced data alongside their evaluation of final build quality. Through this approach, data was collected within a makerspace and used to correlate chosen novice MEX parameters with the possibility of build failure, which can then be used to offer preventative measures and support for future students in the space. This, in turn, offers the possibility of better supporting student efforts, reducing the potential for frustration, and ultimately improving learning outcomes.

2. Literature Review

To contextualize the proposed framework and educational tool in this paper, it is necessary to explore both the roles of makerspaces and MEX in AM education, as well as the potential to use crowdsourcing as a path for AM support.

2.1 The Role of Makerspaces in Engineering Education

Makerspaces are an essential part to the Maker Movement, a growing phenomenon that incorporates hands-on experience into learning regardless of the skill level of its patrons, allowing for participants of all ages to make, learn, and grow. A study at the University of San Diego found that formal learning spaces such as classroom-based machine shops can be daunting and unengaging to students, especially novices [10]. By contrast, makerspaces that act as informal learning spaces, unrestrained and open-minded, contribute to a more welcoming and creative environment [11]. A core value of makerspaces is their inclusive nature, a goal that many spaces strive to maintain and thus employ welcoming philosophies as to attract and retain their student body [2, 12]. Dedicated programs, trainings and staff within a makerspace are typically present to provide assistance to those who request it; however, it has been found that self-guided learning and the personal experience of exploring how to make within a makerspace have a positive effect on a student's confidence in design and engineering [13, 14].

Beyond this, research consistently demonstrates that makerspaces in engineering education yield quantifiable improvements in students' design and manufacturing capabilities. As an example, students who engage with makerspaces have self-reported improvements in their creativity, whereby they can apply engineering concepts to tangible products [15]. Faculty echo this sentiment, noting that the rapid iteration enabled by makerspaces can foster not only students' creativity, but also their critical thinking [16]. This is bolstered by the notion that makerspaces are able to provide students with an authentic design context in which to develop their skills [17]. Studies have also shown that students who engage early and frequently in makerspaces exhibit greater engineering design self-efficacy, which may result in greater proficiency in translating design concepts into functional prototypes and manufacturable designs [18, 19]. Additional evidence suggests that the hands-on experience with digital fabrication technology in a makerspace can effectively support a deeper understanding of manufacturing process types and the range of crucial constraints that go along with them [20, 21]. Ultimately, this evidence supports the crucial role that makerspaces play in modern engineering education as a conduit for hands-on, self-guided learning.

2.2 MEX as a Central Piece of Makerspaces and AM Education

The philosophy of self-guided learning in a makerspace holds true for each piece of equipment that the student works with, including MEX machines. AM machines, especially machines that make use of MEX, continue to be one of the most common technologies associated with makerspaces [8, 9, 22]. Makerspaces can provide a more profound and foundational MEX learning experience for novices than they might find in traditional classroom lectures, due to the makerspace's dependency of hands-on experience as the primary function of teaching. Because of the rise of AM and MEX in many industries in recent years, universities and even K-12 schools offer lectures and entire courses focused on AM, providing knowledge of the technology [23, 24]. These courses focus largely on the theoretical and advanced side of AM, but not necessarily hands-on learning where the student can apply the taught knowledge, as opposed to a makerspace where the student would regularly interact with the machine and employ self-directed learning [23, 25]. An observational study in a makerspace with casual learners, those without proper training or experience, showed that inexperience with AM related processes, tools, and software can lead to print failures becoming a regular part of the experience, where the student would have to learn what they did wrong [6]. Learning in community-focused makerspaces is a hands-on process of experimentation where the student will encounter failure and be prepared to learn from their mistakes and try again [26, 27].

Previous research has shown that, even when presented with formal design for AM educational content, novices may still often rely on trial and error, resulting in a range of potential part defects [28]. Though trial and error is a recognized path for novices to learn MEX, failures can be a problematic part of the experience and should be minimized in their severity to lessen the student's frustration with AM and reduce the frequency of machine maintenance. A failed MEX tray can serve as an opportunity for learning more about the printing process; however, an unsuccessful part can be a hindrance to the student's timeline, budget, and disposition, while also causing the makerspace increased filament waste, staff time, and maintenance. The previously mentioned observational study with casual learners shows that instances where AM novices encounter tray failures can cause the student to become upset and on occasion, significantly decrease their interest in AM; this is not unique to novices but can apply to all students of AM [6]. It would be beneficial to develop a tool that could discover where makerspace novices regularly encounter failure so counter measures can be applied to improve their learning without hindering the makerspace, its staff and other students.

2.3 Current Practice of Crowdsourcing AM Information and Collection of Failed Trays

With the large number of novices routinely entering university makerspaces, crowdsourcing offers a unique opportunity to collect massive amounts of information regarding MEX tray successes and failures. Crowdsourcing is a way of finding a solution to a significant problem through the means of outsourcing the task to a specific crowd and collecting vast amounts of data in return for some reward [29, 30]. This reward may be intrinsic, where the crowd participates knowing that the data will be collected and utilized for a good reason, or extrinsic, where the crowd participates because there is some monetary prize or acknowledgement [29, 31]. The key benefit of using crowdsourcing here is that the data provided will give a better understanding of the common failures occurring within a specific makerspace with their target consumer group: novices [32]. There have been crowdsourcing studies performed that collect design information from novices and compare results to expert opinions. The results illustrate how a novice crowd's opinion comes close to expert judgement, yet the novice crowd is easier to access and collect information from [33, 34].

Collecting design information regarding AM is not new; past studies have aggregated data from STL and G-Code files from students, which enables researchers to connect the information to MEX tray failures to a certain extent. Bacciaglia et al used a MATLAB script to read through each line of a MEX tray's G-Code and extract information from lines that contain certain triggers; from this they were able to create 3D models that accurately represented the printed part [35]. A survey was done by Song and Telenko in the Georgia Institute of Technology makerspace, where print failure information was collected and correlated to the amount of experience that the student has with computer-aided design (CAD) modeling and AM processes [36]. The results did not show a strong correlation between experience and the chance of a tray failure. However, they had an overall small sample size, and a significant portion of their part files were downloaded from experts online. It is challenging to claim these parts to be expertly designed when others have had immediate issues producing Thingiverse.com models, undermining the desired connection between the designer's experience level and their CAD models. The limitations in previous work present an opportunity where a crowdsourcing-based tool would thrive in capturing novice MEX information by taking place within a makerspace, where a rich source of novice AM students exists.

3. Framework for Identifying and Collecting Failure Information to Support Student Learning in a Makerspace

With the opportunity to crowdsource MEX information from students in a makerspace for correlation with build quality and success, two efforts are required. The first is to identify and categorize the potential factors that drive build quality in MEX systems. Secondly, it is necessary to establish a robust means to collect student build information to create a crowdsourced database of build quality for analysis, synthesis, and distillation into usable guidelines to support student learning.

3.1 Identifying and Categorizing Potential Factors in Build Quality

Many parameters in the MEX process affect fabrication, some to the extent that a build fails entirely, while others may only leave features less detailed. Though there are many possible error sources in an MEX tray, they can be sorted into one of four categories that characterize the MEX process chain as relevant to makerspace use: (1) the part's design, (2) the slicing process, (3) the machine system used, and (4) the student's actions during the physical printing process [6, 36–38]. Variables can be described further based on the impact each has on a build, broadly separated into affecting (1) printability, (2) functionality, or (3) quality. Large effects in these categories can cause the entire part to fail, moderate effects can change how functional a piece is, and minimal effects may only change the object's quality [6, 28, 29]. A fishbone diagram, seen in Fig. 1, was constructed to discretize possible factors driving failure into the four categories. Parameters are shaded to signify that they are characterized to affect the tray's printability, functionality, or quality, respectively. The level of severity for each parameter was selected based on previous research and guidelines provided by MEX machine companies. It should be noted that parameter severity may differ from machine-to-machine and personal interpretation. Specific factors underpinning each category are discussed in turn.

Part Design Factors: This first category encompasses features detailed in the part's design, such as thin walls and the STL resolution. For example, if a printed wall exceeds a prescribed height-to-width ratio, the feature can collapse mid-print due to buckling, causing a printability failure that cannot be resolved during the MEX process [39]. An STL file holds the surface information by estimating features with triangular faces; as such, the precision of the part's geometry depends on the set resolution and can therefore cause the print to lack details [40]. Compared to the previously discussed point of failure, the likely effect of poor resolution is inadequate quality, not outright failure of the build.

Slicing Factors: This second category includes settings selected in the slicing software, such as the use of support material and the prescribed infill percentage. As with Part Design Factors, the impact of such factors on the success of a build can be varied. For example, support material may negatively affect surface quality of the created part but may be necessary for proper fabrication [41]. By contrast, the infill amount has minimal effect as to whether the part will fail during the printing process but largely accounts for its strength and thus its functionality [42].

Machine System Factors: The third category includes characteristics of the MEX machine, such as the nozzle condition and diameter. For example, since filament must by necessity flow through the nozzle, a clog makes it impossible to extrude material and thus acts as a severe factor on printability. The nozzle diameter contributes to the surface quality of the printed object, where a smaller nozzle diameter can print finer details and may reduce the overall surface roughness [43].

Student Interference Factors: Students can additionally interact with the MEX process while the part is being fabricated and change settings that may significantly impact the process. Such interference could include adjusting the temperature of the nozzle or the speed at which the machine extrudes. The nozzle temperature needs to be within a certain range around the melting point of the filament material, too cold and it cannot extrude, too hot and it will fail to retain its shape. The speed of the extruder can affect the object's tensile modulus, thus affecting its functionality [44].

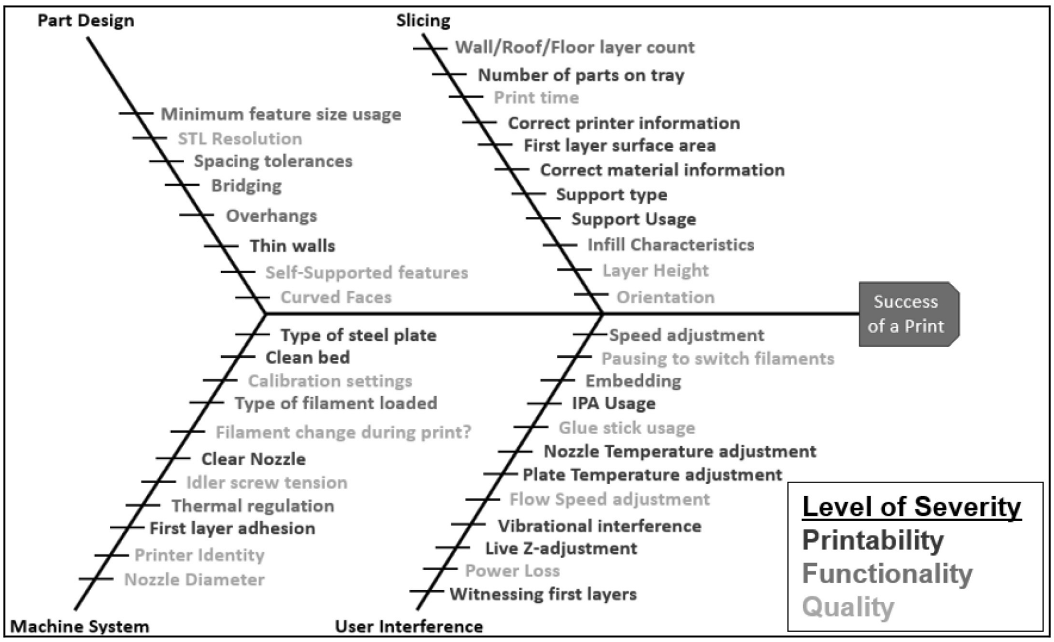

Fig. 1. Fishbone diagram of parameters that can affect the success of an MEX tray. Different greyscale fonts signify the overall severity, affecting either printability, functionality, or quality, respectively.

3.2 Collecting Relevant Build Information to Establish a Crowdsourced Quality Database

With potentially impactful parameters identified, a method of collecting the selected metrics from student users of the makerspace is necessary. One possible approach is to create a questionnaire that asks students to detail their selected MEX process variables and satisfaction of the finished build. However, by minimizing the number of questions asked of the students, their mental load can be reduced, which may positively influence the number of submissions, creating a richer dataset from which to develop supporting guidelines. Certain variables, such as slicing software metrics, leave a footprint in the build's G-Code and can be extracted through software such as MATLAB without having to request input from the student. However, because the assessment of how the MEX tray finished naturally requires the student's perspective on printability, functionality, and quality, questions regarding how well the parts were fabricated will need to be answered by the student, as will any parameters adjusted during the printing sequence.

To increase the likelihood of students completing the survey, a MATLAB script was formulated to extract metrics that are stated in the prepared G-Code, leaving only necessary questions for the student. Data was gathered in two ways: (1) through submission of their G-Code and (2) by answering questions about their finished MEX build. Students are meant to complete the questionnaire immediately after the build is manufactured and their parts are picked up. This method was selected to ensure that any characteristics of the build quality reviewed by the student are due to the printing process and not from anything after the fact, such as a broken elements due to handling or transportation after printing. A flowchart, shown in Fig. 2, was created to visualize how data collection happens and the order in which the student answers the questionnaire.

Automated Data Collection from G-Code: The student begins the questionnaire by uploading their PrusaSlicer generated G-Code file for their current tray. To maintain anonymity of submissions, students are given a randomized name to use for their build file. A MATLAB script is then used to search for and store slicing process variables of interest spelled out within the G-Code.

Manual Data Collection from Students: After uploading their G-Code, students answer a few introductory questions including the MEX machine used, whether a filament change occurred, and if any parameters were adjusted mid-print. By asking these few questions, multiple MEX parameter values can be inferred and collected. Fig. 3 illustrates how the questions appear to the student in the Qualtrics questionnaire. The final question of the introductory section that every student answers is how many objects were being fabricated on this tray and which of them, if any, failed to complete. In the case of one or more objects failing to print, the survey begins posing questions directly related to printability outcomes; otherwise, they proceed to be asked questions about part functionality.

Within the printability question set, the student is first asked whether the MEX machine experienced any vibrational impacts [38] or registered errors. The Prusa MEX systems used in the student-centered makerspace in this work may display registered errors indicating problems with the G-Code's

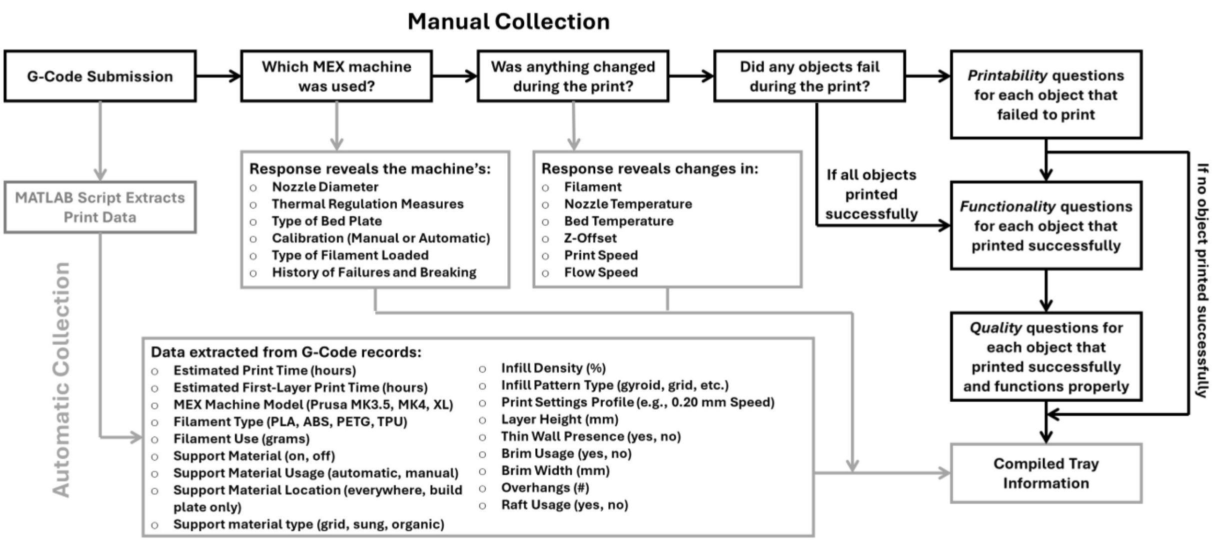

Fig. 2. MEX tray survey flowchart, showing the progression of the questionnaire and where data collection occurs. The black outlined boxes represent the students' survey responses, whereas the grey outlined boxes show automatic collection.

slicing or a malfunctioning machine. Then, for each object that failed to fabricate, the student is questioned when, where, and how the failure occurred. Understanding how the part failed is important information that only the student can answer, which can help reveal the source of fault. For example, an object failing within the first few may indicate low adhesion to the build plate, caused by an unclean plate or a small surface area of the part serving as the foundation [37, 38].

Upon completing the printability questions, for each part that failed to print the student is next asked if each part has an intended function and, if so, whether each seems to function properly. If the part does not function properly, the student is asked to detail the reason, which can help reveal the fault to be either in the design phase or slicing settings. If the part either has no intended function or functions correctly, then the student is asked about the quality of the part. If satisfied with the result, the questionnaire ends, otherwise they must select why they are displeased with the part. Students are presented with visual examples of common quality defects to help them better identify and describe issues with their parts (as seen in Fig. 3). These results can then be analyzed to determine which parameters have a large effect on the printed part. The completed questionnaire answers can then be compiled and downloaded into an Excel spreadsheet containing data from all submissions. The corresponding G-Code files are downloaded into a zip-folder, due to their large size, which can then be extracted and examined later.

It is worth noting that, within this initial crowdsourcing approach, potentially impactful parameters related to design (as seen previously in Fig. 1) are omitted. This is due to the fact that this information cannot be automatically extracted from the uploaded G-Code in the same way that other parameters can. To accurately capture design information, it would be necessary to either have the students self-report key design parameters in their parts or to automate the extraction of design data from an uploaded STL file. The latter is currently challenging to do outside of voxel-based analysis. As such, implementation in the current survey format would require students to self-report, which could further increase their cognitive load and reduce their willingness to complete the survey central to this research. In the end, the research team elected to focus efforts on demonstrating the proposed data collection and correlation technique using more easily obtained data. Future efforts, outside of the scope of this paper, will focus on collecting design parameters to create a more robust crowd-sourced data set.

4. Capture and Analysis of Crowdsourced MEX Build Data

Once the questionnaire structure and corresponding MATLAB extraction code was crafted, collection of makerspace MEX builds began. With approval of the Penn State Institutional Review Board, 118 builds from the Pennsylvania State University College of Engineering makerspace were collected and analyzed. Though this sample is but a subset of the total number of builds that are processed through the makerspace in a semester, it nevertheless offers a sufficient dataset with which to demonstrate the viability of crowdsourcing student guidance in support of AM use.

4.1 In-Situ Study Setup

Survey participants in the selected makerspace were recruited by posting flyers near the Prusa MEX

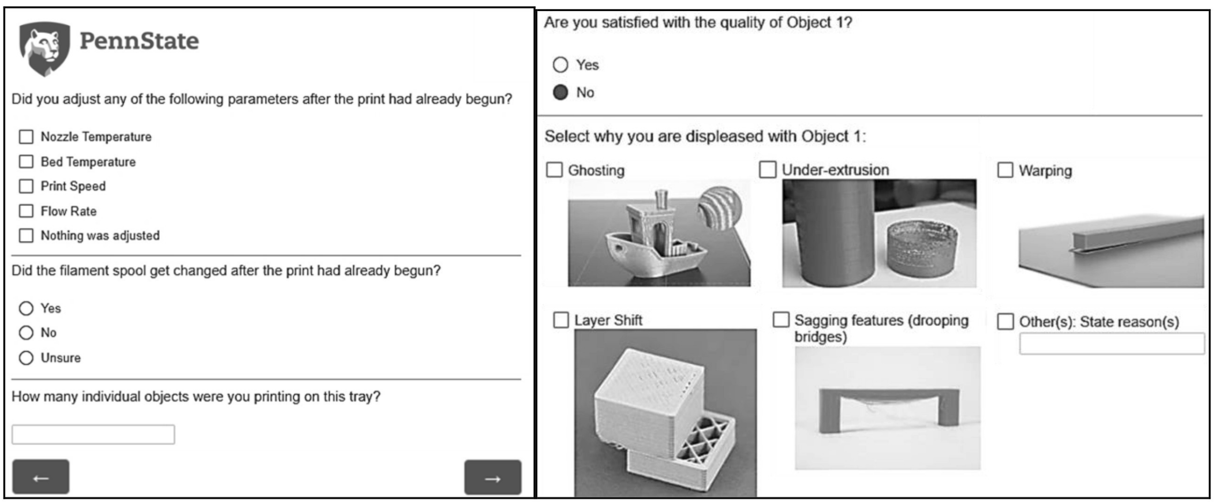

Fig. 3. Example questions posed to students in the Qualtrics questionnaire.

machines within the makerspace, offering points redeemable toward branded makerspace merchandise for completing the optional survey. Students were asked to take the survey on a device that could upload the prepared G-Code, typically their computer. Because of this, the research team elected to avoid using a generated quick-response (QR) code to access the survey, since it may be difficult to scan through a computer camera. Instead, a short website link generator was employed to reduce the effort of the students finding the Qualtrics survey.

For each submitted G-Code and students' answers to the questionnaire, the information was inspected within MATLAB, as discussed previously in Section 3. All statistical analyses of this data set were performed in R Studio using LASSO regression, which are discussed here in turn. It is crucial to note that, to use the MEX machines at the makerspace, two requirements must be met. One, the student is a person affiliated with the university and two, the student is first required to complete an online safety quiz. After completing the safety quiz, the Prusa MK3.5 machines can be used in the open-access space; these are limited to PLA material and require the student to remain during the entire fabrication process. Through additional makerspace training, access to more materials and the Prusa MK4 and XL machines can be granted in the more constrained shop space. Though students remained anonymous, it can be inferred from the responses that, if an MK4 or XL machine was utilized, at least one of the trainings was completed.

4.2 Results and LASSO Regression

Prior to initiating statistical tests on the collected data, the MATLAB output data needed to be formatted. Several variables were created and formulated due to students incorrectly slicing their parts on a systematic level, including whether the machine and material being used match that selected in the slicer. For example, there were several instances where a student sliced their tray for the Prusa MK4 but were in fact using an MK3.5. Additionally, builds with multiple parts were split apart into their distinct parts, to both understand how chosen MEX parameters influence individual parts and to increase the size of the collected sample to improve the accuracy of the model being used to help establish the supporting guidelines.

In R Studio, the data was sorted into categories, including for each dependent variable of interest: (1) a data set containing every build with a success/fail value, (2) a data set containing every individual part with a success/fail value, and (3) a subset for when support material is used. These distinct data sets are necessary for analysis due to certain variables appearing in specific circumstances; for instance, "Support Material Style" can only be investigated when the support material is activated. Table 1 shows the distribution of build data submitted by students during the collection period. The total values in Table 1's printability column represent all parts/trays for the given row; for example, there were 153 parts total that used support material, and of those, 127 were fabricated and thus succeeded in printability. Of those 127 parts, 100 had an intended function and 98 of them functioned properly. For those same 127 parts that either passed printability and had no intended function, or had an intended function and worked properly, 121 of them had a satisfactory quality. At the "Build Tray" level, successful builds regarding printability, functionality, and quality were defined to be builds where all parts on a tray were successful for that category.

With broad success of printability, functionality, and quality tabulated, there is still a need to see how specific factors of interest from Fig. 1 affect the likelihood of print success along any of these three dimensions. To achieve this, Least Absolute Shrinkage and Selection Operator (LASSO) regression was selected for the statistical method for this study because of its ability to handle many variables of interest, avoidance of overfitting for small data sets, and circumvention of multi-linearity issues.

Table 1. Distribution of success and failure for trays and individual parts submitted by students categorized by printability, functionality, and quality

Distribution of In-Situ Data Collected				
		Printability	**Functionality**	**Quality**
Individual Parts	Success	198	144	175
	Failure	30	2	23
	Total	228	146	198
Individual Parts w/Support	Success	127	98	121
	Failure	26	2	6
	Total	153	100	127
Build Trays	Success	67	49	52
	Failure	10	2	15
	Total	77	51	67

Table 2. Results of LASSO regression for in-situ study with positive changes and negative changes noted

	Independent Variable of Interest			**Dependent Variable Transformed Coefficient**		
	Predictor Variable	**Selected Value**	**Comparison Value**	**Printability**	**Functionality**	**Quality**
Build Trays	Estimated Print Time	Time (for 1 hour increase)	N/A	–	–	–
	Estimated First Layer Time	Time (for 1 hour increase)	N/A	–	–	–
	Filament Use	Amount (for 1 gram increase)	N/A	–	–	–
Individual Parts	Parameters Adjusted Mid-Print	True	False	+57%	–69%	–78%
	Printer Model	MK4	MK3.5	+1076%	–	+153%
		XL		+52%	–	–
	Slicer and Printer Model Match	True	False	+260%	–	–68%
	Slicer and Filament Match	True	False	–	–	–
	Filament Type	Generic ABS	Default	+73%	–	–
		Generic PETG		+569%	–	–90%
		Generic PLA		–	–	–
		Hatchbox PLA		–	–	+400%
		Prusa ABS		–	–	–
		Prusa PLA		+475%	–	+520%
	Support Material	On	Off	–4%	–49%	+23%
		Placement: Manual	Placement: Automatic	–	–	–
		Location: Everywhere	Location: Build Plate	–76%	–	–99%
		Style: Organic	Style: Grid	–32%	–	+109%
		Style: Snug	Style: Grid	–	–	–99%
	Print Settings	0.20mm, Speed	0.10mm, Fast Detail	–93%	–62%	–97%
		Other	0.10mm, Fast Detail	–	–	–
	Brim On	True	False	+220%	+158%	+103%
	Infill	Amount (for 1% increase)	N/A	See (Eqn. 1)	See (Eqn. 1)	–
		Style: Other	Style: Grid	–56%	–	+25%

LASSO's use of the lambda shrinkage operator causes variables with little to no effect to have a zero-value coefficient; therefore, only variables with significant effects remain. Coefficients for each independent variable were generated and represent the change in log-odds of the dependent variable. To better understand the effect of each independent variable, these coefficients can be converted to represent the change in odds of success of the dependent variable. The transformed coefficients relate the independent and predictor variables and can be seen in Table 2 in their percentage increase-of-odds form.

Having a predictor variable with the selected value instead of the comparison value, while keeping other variables constant, leads to a percentage increase in odds for printability, functionality, or quality for that dependent variable. For example, activating the brim leads to the odds of success increasing 220% for printability, 158% for functionality, and 103% for quality. Cells in the table without numerical values represent that there was no significant effect of the row's predictor variable on the column's dependent variable, or that no analysis could be done because there were too few instances of this predictor variable used. Additionally, several predictor variables are not binary, but continuous, meaning that there is no simple "activated" state, but a distribution of levels; because of this, there is no single resulting coefficient that states its effect on all value increases. The continuous variable with a significant effect in this LASSO model is infill percentage, so for any increase in infill, the following equation can be used to determine the negative effect for both printability and functionality.

$$\textit{Decreased Odds of Success} = \left(1 - e^{-0.03 * (\textit{Infill Percent Increase})}\right) * 100\% \qquad \text{(Eqn. 1)}$$

For instance, a 1% increase in infill leads to 3% decreased odds of success for printability and functionality, and a 10% increase leads to 28% decreased odds of success.

4.3 *Implications for Printing and Student Guidance in the Makerspace*

As mentioned previously, it was necessary to have several data groups for each dependent variable, including one specifically for entire builds, because predictor variables such as print time and material use regard the entire tray and not each individual part on the tray. However, as shown in Table 2, variables related to the entire build tray did not have a significant effect on the success fraction of printability, functionality, or quality. All significant effects on dependent variables arose from looking at individual parts; notably, there were several distinct independent variables for each dependent variable that had a significantly larger impact on the student-evaluated outcomes. For each significant predictor, the results will be discussed here in turn.

Printability Results: The variables that had the greatest effect on the printability of parts included the machine model used, filament type, brim use, and support material location. Regarding which model of MEX machine to use, MK4's and XLs showed an effect of increasing the odds of success by 1076% and 52%, respectively. Though these models being newer may improve printability, a confounding variable exists that requires further clarification. As mentioned previously, the MK4 and XL models require additional training, which provides a tutorial to properly use the slicing software. Thus, this data may show that the trainings themselves may have a positive effect on the outcome of the build and not necessarily the machine model alone.

If the student skips the initial PrusaSlicer configuration wizard, the desired parts will be sliced under a "default" preset. This "default" filament preset causes the system to preheat to lower temperatures compared to the "Generic PLA" preset; this lacking heat can cause an adhesion failure [36]. When compared to "default", using "Generic ABS," "Generic PETG," and "Prusa PLA" improve the odds of success by 73%, 569%, and 475%, respectively. This stands to reason that regardless of the filament type loaded in the machine, slicing under either of these three presets is a better investment than using "default." If the student chooses the incorrect filament in the slicer, this can lead to a significant failure that causes material to clog around the nozzle, as seen in Fig. 4 (left). However, the distribution of filament usage, as seen in Fig. 5, shows that only two trays each used "Generic ABS" and "Prusa PLA." When independent variables have too few occurrences, the results can become unreliable, and in this instance regarding filament types, the results are limited by the lack of data. If the student activates the brim and leaves all other parameters constant, they can improve the odds of printability success by 220%. By increasing the surface area of the first fabricated layer with this sacrificial material, brims can assist in preventing delamination from the tray mid-print. For example, Fig. 4 (right) shows a part that failed in printability by losing adhesion to the tray during the printing process and did not have a brim activated, despite having a large height to width ratio.

Finally, by selecting the support location set to "Everywhere" instead of "Support On Build Plate Only," the student decreases the odds of success by 76%. Having the location set to "Everywhere" has PrusaSlicer determine all features needing support and builds it stemming from directly below the feature, regardless of whether that causes material to be placed on top of the model. "Support On Build Plate Only," however, forces support material to not build from on top of the model. While this can possibly cause certain areas to become unsupported because not all features can be reached from the build tray, this may not come to pass depending on the chosen geometry being printed.

Functionality Results: As seen in Table 2, the only variable that had a positive effect on the functionality of parts was activating the brim, whereas

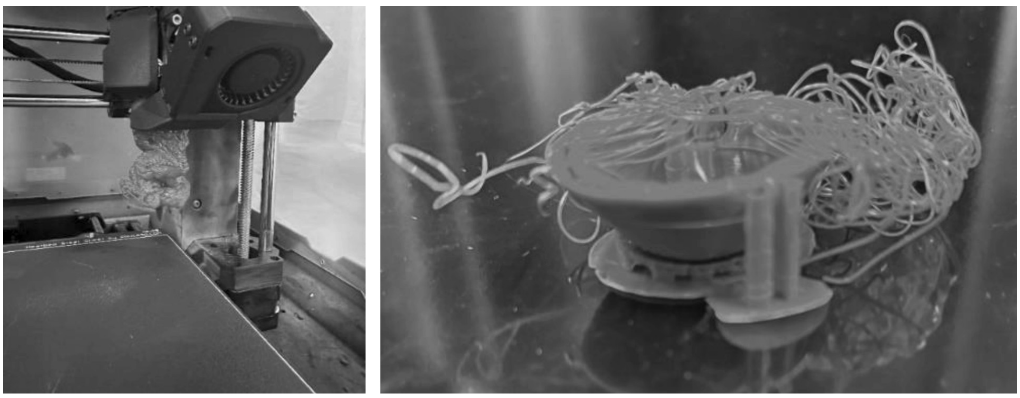

Fig. 4. Large material clog as result of incorrectly slicing the proper material option (left) and sample part printed with support material active but no brim, resulting in delamination and a printability failure (right).

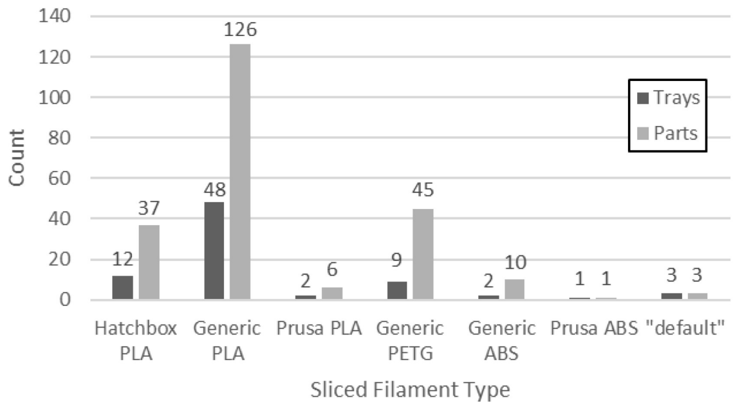

Fig. 5. Distribution of makerspace filament type usage.

adjusting the parameters mid-print, activating support material, selecting "0.20mm, Speed," and increasing the infill amount led to a decrease in odds. As seen in Table 1, of the trays that had a function, only 2 out of 51 builds failed at achieving that functionality. Setbacks were encountered when performing LASSO analysis for functionality and because only 2 out of 146 parts failed; as such we are unable to draw significant conclusions from LASSO regarding functionality. However, the low number of reported failures does suggest that students in the space were generally able to fabricate functioning MEX parts in the makerspace when desired and encountered little failure in this metric of build success.

Quality Results: The variables with the greatest effect on the quality of individual parts include the selected filament, mid-print adjustment, support material usage, and print settings. Instead of using the "Default" material setting, by selecting "Prusa PLA" or "Hatchbox PLA" the student increases the odds of success by 520% or 400%, respectively, whereas selecting "Generic PETG" decreases the odds of success by 90%. Understandably, selecting a filament preset instead of "Default" will create better parts, as previously discussed for printability; however, the selection of "Generic PETG" decreasing the odds of success so dramatically comes as a surprise. Only two parts sliced under "default" preset, and both were successful in quality, whereas selecting "Generic PETG" had a quality success rate of 64% with 45 parts. If more data were collected using "Default," it is possible that more failures would occur and this large PETG effect would likely diminish.

The student adjusting parameters mid-print decreases the odds of quality success by 78%. Of forty parts adjusted mid-print that passed printability and functionality, fifteen were deemed unsatisfactory in quality; however, these all came from the same tray and had the same adjustment, a set speed of 200%. A speed increase may cause the motor axis to become misaligned and cause a layer shift, which was the reported issue for these evaluated parts. Notably, the support location of "Everywhere" instead of "Support On Build Plate Only" decreased the chance of quality nearly entirely. In total, there were 35 parts from 7 trays with the support location set to "Support On Build Plate Only" and only 1 of those parts failed the quality assessment. If more data were collected, the severity of its effect would likely decrease. Similarly, the student choosing the style "Snug" instead of "Grid" decreased the odds of success nearly entirely. The "Snug" style typically uses less material than "Grid," which may have a faster print time, but it can also make supports harder to remove and less stable, resulting in poorer overall quality. Similar with printability, selecting "0.20mm, Speed" instead of "0.10mm, Fast Detail" led to a significant decrease in quality success. Thinner layers and slower speeds as used in the "0.10mm, Fast Detail" preset can allow for more detailed features which can more satisfactory to the student. Only 28 out of 198 parts judged for quality were sliced with the "0.10mmm Fast Detail" preset, and all were acceptable in quality to the students. However, these stem from only 4 unique trays which diminishes their overall significance.

An unexpected result from LASSO regression was that having the slicer and printer models match properly actually caused negative effect on quality success. Such a mismatch would be recorded if the student sliced a build for a MK3.5, but the model used was actually an MK4. However, such a mismatch would also be recorded if the tray was sliced for an XL with the wrong number of toolheads, which did occur on several builds; it may be that for this specific kind of mismatch, the effects are minimal compared to slicing the tray for an entirely different machine model. Because different model machines have different dimensional limits and set velocities, it is not recommended for students to purposefully select the wrong printer model to improve the build's quality.

Discussion of Overall Build Success: Several variables have been discussed in their effect on printability, functionality, and quality success. However, a few key parameters had an overall positive or negative effect that emphasizes their significance for helping to guide students in an open-use makerspace like the one observed in this study. By activating a brim, all dependent variables' chances of success increase by at least double, and with a brim's limited additional material use, it is recommended to emphasize that student' activate it whenever possible. Further, if enough time is available, the data suggests that it is beneficial for the students be guided to select "0.10mm, Fast Detail" print setting in that it creates stronger and more detailed parts and will likely improve their perception of the build's final quality. These recommendations are commonly encouraged in the AM community when troubleshooting build failure or dissatisfaction with printed parts, but this study shows that these same build recommendations can successfully be identified through crowdsourcing in a makerspace with a limited number of novice responses.

Overall, this study representing MEX use in this makerspace is not without limitations. From informal observations, there have been instances where students will not submit all attempts to fabricate a specific tray. Not all, or any, of these initial failed attempts may have been submitted, and instead, only the successful iteration could have been. This is possible and likely, given that the number of reported failures were limited in this data collection. Additionally, though the makerspace used in this study is generally representative of novice AM students, MEX experience is not necessarily uniform throughout the space. As discussed, to use the MK4s the students must attend an AM training held by teaching assistants in the makerspace. Additionally, to use different materials and the Prusa XLs, the students must attend yet a second training. Though the people who enter the makerspace can be broadly classified as novices, it is unreasonable to assume that they retain the same level of experience and knowledge after the required training. As such, data which involves the more advanced MEX models or materials outside of traditional PLA may be confounded with differences in student experience.

4.4 How to Better Support Makerspace Novices in MEX

The results found through the in-situ study reported in this work can accomplish more than just revealing which parameters student users should select when preparing and running a build. 118 submitted makerspace builds allow us to begin understanding of where students unfamiliar with MEX may encounter failure and success. In turn, we can use this new understanding to develop insight into how students could be better instructed to have a more positive learning experience. As discussed in Section 2, students will often learn MEX through trial and error normally; however, encountering failure can lead to negative experiences and frustration with AM. The information learned through this study can be implemented in a way that assists in reducing the number of failures seen in novice builds, while still encouraging a philosophy of "learning through doing" that makerspaces tend to employ. From an engineering education perspective, these findings support constructivist principles by enabling students to build knowledge through experience while minimizing excessive, and potentially frustrating, failure. Structured interventions informed by the empirical data captured through the crowdsourcing efforts in this paper can help novices progress from basic operational skills toward higher-order design and manufacturing competencies.

For instance, a failure commonly encountered in this study was the tendency for parts to become unadhered to the tray mid-print, causing an issue that cannot be resolved during the printing process. This can happen for a number of reasons but commonly has to do with the sliced part having a small amount of surface area interacting with the build tray. These commonly faced problems may suggest that students are manufacturing MEX builds in poor orientations, designing parts with small or highly curved surfaces, or simply not choosing the best suited slicer settings. However, with the findings from the crowdsourced data, the makerspace could emphasize the most beneficial information to avoid build failure in a concise manner before students use the MEX machines. Similarly, from the crowdsourcing it was identified that activating a brim increased the odds of printability success and improved part quality, all with minimal material cost. This is an easy adjustment that can be taught early to novices to improve their learning. Avoiding excessive infill was also found to be critical, since the data showed that in certain cases increases in infill can reduce the odds of success, reinforcing student lessons on resource efficiency. Embedding these insights into validated slicer profiles for students could ideally reduce students' cognitive load and allow them to focus on growing their conceptual understanding of AM rather than troubleshooting avoidable errors. Despite the makerspace in this study offering training covering MEX in a great deal, failures were still encountered in these more restricted spaces that could have been minimized. The conclusions drawn from this data encourage the training to be revised to focus more on the issues brought to light. For other makerspaces that do not have MEX trainings, this knowledge can be used on a wider scale to provide any novice-filled makerspace with validated advice for those unfamiliar with MEX. Integrating these findings into structured guidance can ensure that students spend less time on repetitive failure and more time engaging in iterative design and functional prototyping, which are the key drivers of makerspace use in engineering education.

Novices attempting to use unfamiliar equipment already take a step outside their comfort zone and may not ask for help immediately. Therefore, it is up to the makerspace to meet novices halfway through providing validated resources that help newcomers both avoid a negative experience and the consequences of build failure. One way to accomplish this would be through visual troubleshooting guides, built off the crowdsourced data discussed in this paper, that illustrate common failure modes and corrective actions to improve print success. Such guides may empower students to self-diagnose issues and could also be paired with structured peer collaboration in the makerspace to further create opportunities for shared learned about printing success and failure. Such approaches align with both active and peer-assisted learning models widely adopted in engineering education, and, in turn, may reinforce technical fluency and metacognitive skills. By embedding the evidence-based best-practices identified through our AM crowdsourcing efforts into an informal learning environment like a makerspace, it will enable the space to function not only as a fabrication hub but as pedagogically rich ecosystem where technical success can translate into meaningful educational outcomes.

5. Conclusions and Future Work

This paper describes the formulation and deployment of a crowdsourcing-based data collection tool that extracts MEX build information to reveal where common sources of success and failure arise in novice trays. The build data is correlated alongside a student evaluation of the MEX tray's performance to provide a range of printing-related information while minimizing inconvenience to the student. Through LASSO regression, the student-selected settings were investigated for their effects on the three dependent variables of every MEX tray: the success of printability, functionality, and quality. Several MEX build parameters were identified in their positive or negative effect on the student's tray, with some having a strict either positive or negative effect, and others having mixed effects. For instance, the study showed that the activation of a brim led to positive increases for all, whereas the activation of support material improved quality but had a toll on the odds of success for printability.

As previously discussed, a limiting factor in the study was sample size. There were several variables that could not be fully analyzed because of the lack of data; there were especially few failed builds collected. Additionally, because of the makerspace's policies regarding training procedures, the in-situ data collected cannot be assumed to be solely from novices, as originally intended. To draw conclusions about the variables whose results were inconclusive in this study and reinforce the results of significant parameters found, more data collection is necessary. Because of the lack of failure data collected, it is recommended that the next data collection reinforces the types of data wanted; both successful and unsuccessful build data is desired to draw accurate conclusions about makerspace builds. Though MEX data was collected, and recommendations can be made, additional information is needed to provide conclusive endorsements to specific MEX parameters that will result in the highest chance of build success.

References

1. M. Thompson, G. Moroni, T. Vaneker, G. Fadel, R. Campbell, I. Gibson, A. Bernard, J. Schulz, P. Graf, B. Ahuja and F. Martina, Design for Additive Manufacturing: Trends, Opportunities, Considerations, and Constraints, *CIRP Annals Manufacturing Technology*, **65**(2), pp. 737–760, 2016.
2. A. Noel, L. Murphy and A. Jariwala, Sustaining a Diverse and Inclusive Culture in a Student Run Makerspace, *International Symposium on Academic Makerspaces*, Cambridge, Massachusetts, 2016.
3. V. Wilczynski, Academic Makerspaces and Engineering Design, *122nd ASEE Annual Conference and Exposition*, pp. 1–18, 2015.
4. A. Kantaros, D. Piromalis, G. Tsaramirsis, P. Papageorgas and H. Tamimi, 3D Printing and Implementation of Digital Twins: Current Trends and Limitations, *Applied System Innovation*, **5**(1), p.7, 2022.
5. S. Abdollahi, A. Davis, J. Miller and A. Feinberg, Expert-Guided Optimization for 3D Printing of Soft and Liquid Materials, *PLoS One*, **13**(4), pp. 1–19, 2018.
6. N. Hudson, C. Alcock and P. Chilana, Understanding Newcomers to 3D Printing: Motivations, Workflows, and Barriers of Casual Makers, *Conference on Human Factors in Computing Systems – Proceedings*, Association for Computing Machinery, pp. 384–396, 2016.

7. ASTM Standard F2792-12a, Standard Terminology for Additive Manufacturing Technologies, http://www.astm.org/Standards/F2792.htm, Accessed 27 October 2025.
8. T. William Barrett and K. Grau Talley, A Review of University Maker Spaces, *122nd ASEE Annual Conference and Exposition*, Seattle, Washington, pp. 1–17, 2015.
9. A. Kantaros, O. Diegel, D. Piromalis, G. Tsaramirsis, A. Khadidos, A. Khadidos, F. Khan and S. Jan, 3D Printing: Making an Innovative Technology Widely Accessible through Makerspaces and Outsourced Services, *Materials Today: Proceedings*, Elsevier Ltd, pp. 2712–2723, 2021.
10. G. Hoople, J. Mejia, D. Hoffoss and S. Devadoss, Makerspaces on the Continuum: Examining Undergraduate Student Learning in Formal and Informal Settings, *International Journal of Engineering Education*, **36**(4), pp. 1184–1195, 2020.
11. C. Forest, R. Moore, A. Jariwala, B. Fasse, J. Linsey, W. Newstetter, P. Ngo and C. Quintero, The Invention Studio: A University Maker Space and Culture, *Advances in Engineering Education*, pp. 1–32, 2014.
12. E. Hilton, S. Smith, R. Nagel, J. Linsey and K. Talley, University Makerspaces: More Than Just Toys, *15th International Conference on Design Education*, American Society of Mechanical Engineers, 2018.
13. M. Koole, K. Anderson and J. Wilson, Unleashing the Learners: Teacher Self-Efficacy in Facilitating School-Based Makerspaces, *In Education*, pp. 63–84, 2020.
14. A. Wong and H. Partridge, Making as Learning: Makerspaces in Universities, *Australian Academic & Research Libraries*, **47**(3), pp. 143–159, 2016.
15. G. Hoople, J. Mejia, D. Hoffoss and S. Devadoss, Makerspaces on the Continuum: Examining Undergraduate Student Learning in Formal and Informal Settings, *International Journal of Engineering Education*, **36**(4), pp. 1184–1195, 2020.
16. C. Lenhart, J. Bouwma-Gearhart, I. Villanueva, K. Youmans and L. Nadelson, Engineering Faculty Members' Perceptions of University Makerspaces: Potential Affordances for Curriculum, Instructional Practices, and Student Learning, *International Journal of Engineering Education*, **36**(4), pp. 1196–1207, 2020.
17. M. Jalal and H. Anis, The Integration of a Maker Program into Engineering Design Courses, *International Journal of Engineering Education*, **36**(4), pp. 1252–1270, 2020.
18. M. Weaver, E. Hilton, M. Aleman, R. Nagel and J. Linsey, Predicting Success of Engineering Student Makers: Relationships Between Makerspace Involvement, Academic Performance, and Engineering Design Self-Efficacy, *International Journal of Engineering Education*, **38**(6), pp. 1851–1861, 2022.
19. E. Hilton, K. Talley, S. Smith, R. Nagel and J. Linsey, Report on Engineering Design Self-Efficacy and Demographics of Makerspace Participants Across Three Universities, *Journal of Mechanical Design*, **142**(10), 2020.
20. P. Taheri, P. Robbins and S. Maalej, Makerspaces in First-Year Engineering Education, *Education Sciences*, **10**(1), p. 8, 2019.
21. M. Galaleldin, F. Bouchard, H. Anis and C. Lague, The Impact of Makerspaces on Engineering Education, *Proceedings of the Canadian Engineering Education Association (CEEA)*, pp. 1–6. 2017.
22. Y. Huang, M. Leu, J. Mazumder and A. Donmez, Additive Manufacturing: Current State, Future Potential, Gaps and Needs, and Recommendations, *Journal of Manufacturing Science and Engineering*, **137**(1), p. 014001, 2015.
23. J. Burke, Making Sense: Can Makerspaces Work in Academic Libraries?, *ACRL 17th National Conference*, Portland, Oregon, pp. 497–504, 2015.
24. J. Go and A. Hart, A Framework for Teaching the Fundamentals of Additive Manufacturing and Enabling Rapid Innovation, *Additive Manufacturing*, **10**, pp. 76–87, 2016.
25. R. Browder, C. Crider and R. Garrett, Hybrid Innovation Logics: Exploratory Product Development with Users in a Corporate Makerspace, *Journal of Product Innovation Management*, **40**(4), pp. 451–474, 2023.
26. V. Wilczynski and R. Adrezin, Higher Education Makerspaces and Engineering Education, *International Mechanical Engineering Congress and Exposition*, American Society of Mechanical Engineers, 2016.
27. M. Richardson, Designer/Maker: The Rise of Additive Manufacturing, Domestic-Scale Production and the Possible Implications for the Automotive Industry, *Comput-Aided Design and Applications*, pp. 33–48, 2012.
28. H. Budinoff and S. McMains, Improving Outcomes and Participation in the Prototyping Process Using Design-for-Additive-Manufacturing Training, *International Journal of Engineering Education*, **34**(4), 2020.
29. X. Niu, S. Qin, J. Vines, R. Wong and H. Lu, Key Crowdsourcing Technologies for Product Design and Development, *International Journal of Automation and Computing*, **16**(1), pp. 1–15, 2019.
30. E. Simperl, How to Use Crowdsourcing Effectively, *LIBER Quarterly: The Journal of the Association of European Research Libraries*, **25**(1), pp. 18–39, 2021.
31. M. Onuoha, J. Pinder and J. Schaffer, *Guide to Crowdsourcing*, 2015.
32. G. Barbier, R. Zafarani, H. Gao, G. Fung and H. Liu, Maximizing Benefits from Crowdsourced Data, *Computational and Mathematical Organization Theory*, **18**(3), pp. 257–279, 2012.
33. M. Green, C. Seepersad and K. Hölttä-Otto, Crowd-Sourcing the Evaluation of Creativity in Conceptual Design: A Pilot Study, *26th International Conference on Design Theory and Methodology*, American Society of Mechanical Engineers, 2014.
34. K. Luther, J. Tolentino, W. Wu, A. Pavel, B. Bailey, M. Agrawala, B. Hartmann and S. Dow, Structuring, Aggregating, and Evaluating Crowdsourced Design Critique, *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ACM, New York, NY, USA, pp. 473–485, 2015.
35. A. Bacciaglia, F. Falcetelli, E. Troiani, R. Di Sante, A. Liverani and A. Ceruti, 2023, Geometry Reconstruction for Additive Manufacturing: From G-CODE to 3D CAD Model, *Materials Today: Proceedings*, **75**, pp. 16–22, 2023.
36. R. Song and C. Telenko, Causes of Desktop FDM Fabrication Failures in an Open Studio Environment, *Procedia CIRP*, **80**, pp. 494–499, 2019.
37. N. Jaksic, What to Do When 3D Printers Go Wrong: Laboratory Experiences, *122nd ASEE Annual Conference and Exposition*, Seattle, Washington, pp. 1–11, 2015.
38. F. Baumann and D. Roller, Vision Based Error Detection for 3D Printing Processes, *MATEC Web of Conferences*, **59**, p. 06003, 2016.
39. R. Wolfs and A. Suiker, Structural Failure during Extrusion-Based 3D Printing Processes, *The International Journal of Advanced Manufacturing Technology*, **104**(1–4), pp. 565–584, 2019.

40. J. Hu, Study on STL-Based Slicing Process for 3D Printing, *Proceedings of the 28th Annual International Solid Freeform Fabrication Symposium*, Austin, Texas, pp. 885–895, 2017.
41. E. Karasik, R. Fattal and M. Werman, Object Partitioning for Support-Free 3D-Printing, *Computer Graphics Forum*, **38**(2), pp. 305–316, 2019.
42. V. Nguyen, T. Huynh, T. Nguyen and T. Tran, Single and Multi-Objective Optimization of Processing Parameters for Fused Deposition Modeling in 3D Printing Technology, *International Journal of Automotive and Mechanical Engineering*, **17**(1), pp. 7542–7551, 2020.
43. P. Wang, B. Zou, H. Xiao, S. Ding and C. Huang, Effects of Printing Parameters of Fused Deposition Modeling on Mechanical Properties, Surface Quality, and Microstructure of PEEK, *Journal of Materials Processing Technology*, **271**, pp. 62–74, 2019.
44. C. Abeykoon, P. Sri-Amphorn and A. Fernando, Optimization of Fused Deposition Modeling Parameters for Improved PLA and ABS 3D Printed Structures, *International Journal of Lightweight Materials and Manufacture*, **3**(3), pp. 284–297, 2020.

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