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AN ASSOCIATION RULE APPROACH FOR IDENTIFYING PHYSICAL SYSTEM-USER INTERACTIONS AND POTENTIAL HUMAN ERRORS USING A DESIGN REPOSITORY

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ABSTRACT

During the design process, designers must satisfy customer needs while adequately developing engineering objectives. Among these engineering objectives, human considerations such as user interactions, safety, and comfort are indispensable during the design process. Nevertheless, traditional design engineering methodologies have significant limitations incorporating and understanding physical user interactions during early design phases. For example, Human Factors methods use checklists and guidelines applied to virtual or physical prototypes at later design stages to evaluate the concept. As a result, designers struggle to identify design deficiencies and potential failure modes caused by user-system interactions without relying on the use of detailed and costly prototypes. The Function-Human Error Design Method (FHEDM) is a novel approach to assess physical interactions during the early design stage using a functional basis approach. By applying FHEDM, designers can identify user interactions required to complete the functions of the system and to distinguish failure modes associated with such interactions, by establishing user-system associations using the information of the functional model. In this paper, we explore the use of data mining techniques to develop relationships between component, functions, flows and user interactions. We extract design information about components, functions, flows, and user interactions from a set of distinct coffee makers found in the Design Repository to build associations rules. Later, using a functional model of an electric kettle, we compared the func-

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tions, flows, and user interactions associations generated from data mining against the associations created by the authors, using the FHEDM. The results show notable similarities between the associations built from data mining and the FHEDM. We are suggesting that design information from a rich dataset can be used to extract association rules between functions, flows, components, and user interactions. This work will contribute to the design community by automating the identification of user interactions from a functional model.

1 INTRODUCTION

Creating and innovating modern engineering systems require more complex problem-solving approaches, which is challenging for current designers. The increasing complexity in consumer products and engineered systems raises the need to support engineers with design knowledge beyond cognitive memory. Traditional product design methods concentrate on designing around an intended end-function of a product. However, evolving global and market needs have influenced modern product design to include complex engineering principles such as sustainability, product life-cycle, and human factors. Commonly, Human Factors Engineering (HFE) methods are treated in isolation from the design process, and they are often incorporated after a design had been defined. At this stage, assessing the final user interactions requires the construction of full-scale physical or virtual prototypes and the application of human-subject data collection. Applying HFE after the design is completed is costly, time-consuming and has its limitations [1–4]. Early identification of failure modes caused by user-system interactions can enhance system performance and safety while reducing design deficiencies due to inadequate consideration of users. Additionally, it can reduce expenses by decreasing the need for developing physical prototypes of the system for validation.

Design approaches that include user considerations during the early design stages can significantly enhance the usability, safety, and comfort of the user [5]. This research aims to support designers by introducing auxiliary design knowledge regarding Human Factors Engineering during design realization. In previous work, we introduced the Function-Human Error Design Method (FHEDM), which is capable of identifying physical user-system interactions and distinguishing possible failure modes caused by erroneous system-user interactions during the early design stages using a Functional Basis framework [6].

In this work, we applied Association rules on an existing Design Repository to establish relationships between *functions*, *flows*, and *physical user interactions* (*user tasks*) to automate the FHEDM. We implement association rule learning using an *Apriori* algorithm to search design data and determine the probabilities of relationships between *user tasks*, *components*, *functions*, and *flows*. These associations can be used to identify user interactions from a functional model, thus facilitating designers to make informed decisions regarding user performance, comfort, and safety.

The remainder of this paper is organized as follows. The Background section introduces design repositories, Association rules, and a short introduction to FHEDM. Next, a formalized methodology and general guidelines for using the method are provided. Section 4 presents the case study used in this work and Section 5 presents the results and discussion. Finally, conclusions followed by recommendations and future work is discussed in Section 6.

2 BACKGROUND

In the following section, we first cover a literature review on Design Repositories, followed by a short introduction on association rules and the *Apriori* algorithm used in this work. Additionally, we introduce the Function Human Error Design Method (FHEDM), how it works and what are the limitations of the methodology.

2.1 Design Repositories

Design repositories are still under development [7] but their impact on data-driven design processes can be valuable. Repositories featuring the collection of design information from a large set of products provides the seed for predictive models to estimate downstream impacts earlier in the design process [8]. Previous research has used different approaches such as driving concept generation through morphology to enable a transition to the use of design repositories in the design of products [8, 9]. Design repositories are more useful than design databases, because they contain more comprehensive information, and provide reliable means of gathering, recording, and storing component data [10, 11]. In this research, we argue that using a Design Repository and association rules regarding information of physical interactions and human errors can improve design novelty and enhance user performance, safety, and comfort.

In this work, we employ the Design Repository[1], hosted by the Design Engineering Lab at Oregon State University, as our focal point of information exchange and design generation tools. The Design Repository contains information for over 130 consumer based electro-mechanical products at various levels of abstraction [9, 10, 12, 13]. In the Design Repository, product information is stored and classified in categories, providing engineers with innovative ways to approach design by enabling the use of data-driven methods to develop insight during the initial phase of concept generation. The Design Repository uses a PostgreSQL database to store product information and data. Figure 1 shows the underlying data schema of the Design Repository. The breadth of information for a product or component is presented

[1] https://design.engr.oregonstate.edu/repo

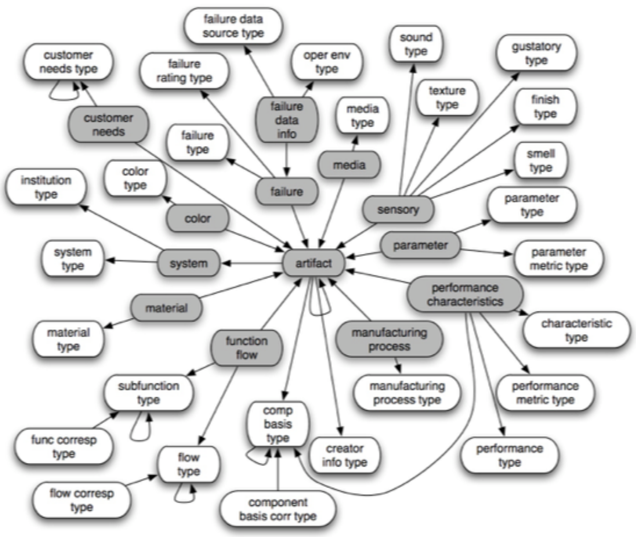

FIGURE 1: Graphical representation of the Design Repository data schema [12]

by the eleven categories containing tables pointing directly to the central component.

Currently, the Design Repository contains over 5000 individual components. Various iterations of the Repository have refined the classification of the components and their functions to follow a standardized taxonomy [9, 10, 13]. In the current state of the Design Repository, there is no information regarding the final user, physical user interactions with the products, and failure modes caused by such interactions. In this research, we expand the Design Repository by incorporating the Function-Human Error Design Method (FHEDM) [6] as a new category of design information by building relationships that include the user, *user interactions*, *human errors*, and their relations with the *components*. We used the functional model and functional basis [14, 15], the component basis [13], and Actionfunction diagrams [6, 16] as the standardized design language.

2.2 Association Rules and Apriori Algorithm

Association rule learning is a rule-based machine learning method that searches information and determines the probabilities of relationships between the variables [17]. The relationships are created by systematically comparing data presented in lists, finding correlations between the items on the lists. In this work, we propose to use an association rule mining to find non-obvious relationships between large datasets, mainly how one choice makes another choice more or less likely [14, 18]. In a canonical supermarket example, a customer buying hamburger buns is more likely to buy sliced cheese to prepare cheeseburgers, which is an illustration of an association rule [19].

Similar to the example described above, we will use association rules within a set of systems in the Design Repository to identify correlations between *user interactions* and within a functional model. This method of data mining determines the patterns in previous product designs that we can use to make rules about how the FHEDM determines *functions*, *flows*, and *components* associations for physical *user interactions* with the product.

One algorithm capable of generating association rules, learning over an itemset, and mining over databases is the *Apriori* algorithm [20]. The algorithm is well documented to be useful for dealing with large datasets and iteratively looks for frequent itemsets [21]. Applying the *Apriori* algorithm in the Design Repository allows us to find correlations and establish relationships between *functions*, *flows*, and *user interactions* for the same *components*. The resulting associations can be used as a set of design principles that indicates the likelihood of design decisions regarding user interactions to specific components and product functions. Associations developed by the *Apriori* algorithm are measured through a probabilistic analysis of items and itemsets using three parameters **Support**, **Confidence**, and **Lift**. For our application, one item can be a *user task*, a *function-flow* a *component* individually, while an itemset is the combination of the items like *component-function-flow*, or *component-function-flow -user task* present in the data extracted from the Repository.

- **Support** indicates the prevalence of an item within all of the itemsets. In the cheeseburger example mentioned earlier, **Support** is the percentage of transaction in the supermarket that contains both hamburgers buns and sliced cheese. Mathematically, **Support** is represented as:

$$Support_{ham \rightarrow ches} = \frac{frequency(hamburgers\ buns,\ sliced\ cheese)}{Total_{transactions}}$$

- **Confidence** indicates the probability of two items appearing in the same item set. In the context of our application, **Confidence** is determined by the prevalence of combinations of *user tasks* with *functions-flow*, and *components*. In the cheeseburger example, **Confidence** is the percentage of transactions in the supermarket, containing hamburgers buns, that also contains sliced cheese. In other words, **Confidence** is the probability of having sliced cheese, given that hamburgers bun is being bought. Mathematically, *Confidence* is represented as:

$$Confidence_{ham \rightarrow ches} = \frac{frequency(hamburgers\ buns,\ sliced\ cheese)}{frequency(hamburgers\ buns)}$$

- **Lift** accounts for the popularity of the *function-flow*, and *component* in the **Confidence** measurement of the combination with *user task*. If a *function-flow*, and *component* set only occurs once but is a majority in its metaset, it could have high confidence value, but **Lift** accounts for this as not to conflate associations by simple prevalence. Continuing with the cheeseburger example, **Lift** is the probability normalized based on the frequency of hamburgers buns being bought as to not be inflated by having a hamburgers buns only being bought once and it happens to be with sliced cheese. Mathematically, *Lift* is represented as:

$$Lift_{ham \to ches} = \frac{Support_{ham \to ches}}{Support_{ham} \times Support_{ches}}$$

2.3 The Function-Human Error Design Method (FHEDM)

The Function-Human Error Design Method (FHEDM) aims to consolidate Human Factors Engineering principles using a functional-basis approach [22] to understand physical user interaction during the early design stage. FHEDM supports designers to recognize product functions that have a direct impact on the user while distinguishing potential failure modes caused by user-product interactions during the conceptual design stage [6]. FHEDM framework, shown in Fig. 2, builds three sets of matrices the Function-User Interaction matrix [FUI], the Human-Interaction Error Matrix [HIE], and the Function-User Interaction Error matrix [FUIE] which are presented in the following subsections.

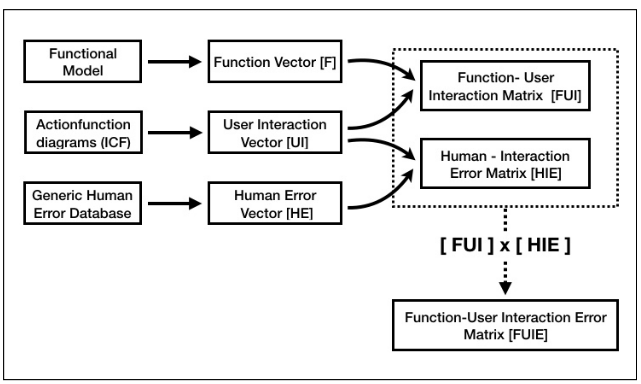

FIGURE 2: Function Human Error Design Method (FHEDM) flow chart [6].

2.3.1 The Function-User Interaction matrix [FUI]

The Function-User Interaction matrix (FUI) is composed using the function m-dimensional vector $[F]$ which captures the set of functions describing the system, and the n-dimensional user interaction vector $[UI]$ which captures the set of physical tasks that the user needs to complete to perform such function. Designers can build the $[m \times n]$ FUI matrix by assigning a number "1" to each cells corresponding to a product function and the physical user tasks that a user needs to complete to perform such function. If no user task is needed a number "0" is entered in the cells.

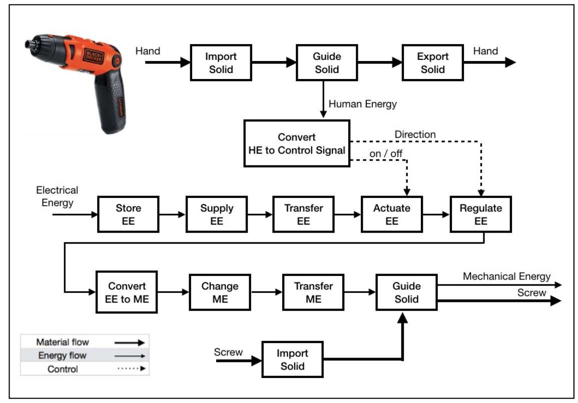

FIGURE 3: Black and Decker electrical screwdriver Functional model

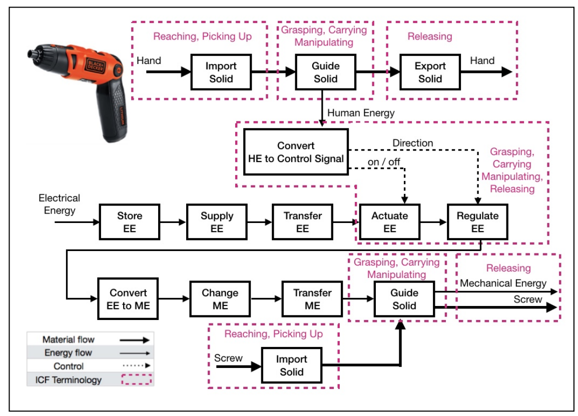

FIGURE 4: Black and Decker electrical screwdriver Actionfunction diagram.

The FUI matrix is manually constructed using the functional model and the Actionfunction diagram of the concept under analysis. To illustrate the formation of the FUI matrix, we present the functional model (Fig. 3) and Actionfunction diagram (Fig. 4) of a Black and Decker (BD) electric screwdriver. The functional model of the B&D electric screwdriver was taken from the Design Repository hosted by Oregon State University (OSU), and the Actionfunction diagram was created by the authors using *ICF lexicon*[2] to describe the user tasks need to complete each function. The *ICF lexicon* was established by the World Health Organization (WHO) to standardized a terminology to describe health and health-related states of humans [23]. The *ICF lexicon* was incorporated as the standard terminology to build Actionfunction diagrams [24]. The resulting FUI matrix for the B&D electric screwdriver can be seen in Table 1.

[2] https://www.who.int/classifications/icf/en/

TABLE 1: Black and Decker electrical screwdriver Function-User Interaction matrix [FUI] [6].

System Functions:	User Task: Reaching	Picking up	Grasping	Carrying	Manipulating	Releasing
Import Solid (Hand)	1	1	0	0	0	0
Guide Solid (Hand)	0	0	1	1	1	0
Export Solid	0	0	0	0	0	1
Convert HE to CS	0	0	1	1	1	1
Store EE	0	0	0	0	0	0
Supply EE	0	0	0	0	0	0
Transfer EE	0	0	0	0	0	0
Actuate EE	0	0	1	1	1	1
Regulate EE	0	0	1	1	1	1
Convert EE to ME	0	0	0	0	0	0
Change ME	0	0	0	0	0	0
Transfer ME	0	0	0	0	0	0
Guide Solid (Screw)	0	0	1	1	1	0
Import Solid (Screw)	1	1	0	0	0	0

2.3.2 The Human-Interaction Error Matrix [HIE]

The Human-Interaction Error Matrix [HIE] is composed using the n-dimensional user interaction vector $[UI]$ which captures the set of physical tasks that the user needs to complete to perform a function, and the p-dimensional human error vector $[HE]$ which distinguishes the possible human errors associated with the user performing a physical task. Designers can build the $[n \times p]$ HIE matrix by assigning a number "1" to each cell corresponding to the human errors that could be present for each of the physical user tasks required to operate the system. If no human errors are present in a given user task, a number "0" is entered in the cell.

The HIE matrix is manually constructed using the user tasks identified in the Actionfunction diagram of the concept under analysis and a generic human error database based on Human Factors Engineering literature. More information about the construction of the generic human error database can be found in the Function-Human error Design Method (FHEDM) [6]. Designers, using the generic human error database, need to identify what are the possible human errors associated with each required user task. The resulting HIE matrix for the B&D electric screwdriver can be seen in Table 2.

2.3.3 The Function-User Interaction Error matrix [FUIE]

The matrix multiplication of the FUI and HIE matrices (Equation 1) construct the Function-User Interaction Error matrix [FUIE]. The resulting FUIE matrix highlights the number of occurrences for a particular human error while the user is interacting with a given function of the concept under analysis. A cell

TABLE 2: Black and Decker electrical screwdriver Human-Interaction Error matrix [HIE] [6].

User Task:	Generic human error - Fail to: Reach specific target	Reach small object	Pickup	Release	Grasp target object	Grasp sliding object	Re-Grasp object	Manipulate	Apply force	Apply pressure	Move to indefinite location	Transfer object to other hand	Move to exact location	Transfer grasped object	Position body	Turn to desired location
Reaching	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Picking up	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0
Grasping	0	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0
Carrying	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0
Manipulating	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1
Releasing	0	0	0	1	0	0	0	1	0	0	1	1	1	1	0	0

with a number greater than "1" presents a potential failure mode caused by a human-system interaction. Designers can identify functions that have a significant number of occurrences and take informed decision to improve the design and avoid such possible user errors.

$$[FUIE] = [FUI] \times [HIE] \tag{1}$$

Table 3 presents the FUIE matrix for the B&D electric screwdriver. From the result, one can distinguish that the higher presence of human errors is located in two groups of functions. The functions associated with activating, regulate, and control the flow of electrical energy present as possible user errors limitations while transforming the force of the hand into a control signal. The functions associated with guiding and exporting the screw and screwdriver presents as possible user errors limitations while transferring objects from one hand to another, and moving the system towards the exact location. Designers can expand on the root of the human error by using the human error database to determine which interaction fallibilities can prevent the user from achieving the desired task.

In the current state of the Function-Human Error Design Method (FHEDM), the results are sensitive to the designers' decisions while developing the FUI and HIE matrices. There are limitations regarding the associations used for matching user interactions with the functions in a functional model. Associations implemented during the first stage of the FHEDM were built by hand using the expertise and experience of the authors. The resulting associations built by the designers will depend on their experience working and understanding functional models, which could create discrepancies between design assessments. Additionally, as the complexity of the design increases, the number of system functions and flows will considerably increase. Form a

TABLE 3: Black and Decker electrical screwdriver Function-User Interaction Error matrix [FUIE] [6].

	Generic human error - Fail to:									
System functions	Reach specific target	Reach small object	Pick up object	Release object	Grasp target object	Re-Grasp object	Manipulate objects	Apply force	Transfer grasped object to other hand	Move to exact location
Import hand	1	1	0	0	0	0	0	1	0	0
Guide hand	0	0	1	1	1	1	0	0	1	1
Export Hand	0	0	0	1	1	1	0	0	2	2
Convert HE to CS	0	0	1	1	1	2	1	0	3	3
Store EE	0	0	0	0	0	0	0	0	0	0
Supply EE	0	0	0	0	0	0	0	0	0	0
Transfer EE	0	0	0	0	0	0	0	0	0	0
Actuate EE	0	0	1	1	1	2	1	0	3	3
Regulate EE	0	0	1	1	1	2	1	0	3	3
Convert EE to ME	0	0	0	0	0	0	0	0	0	0
Change ME	0	0	0	0	0	0	0	0	0	0
Transfer ME	0	0	0	0	0	0	0	0	0	0
Guide solid	0	0	1	1	1	1	0	0	2	2
Import solid	1	1	0	0	0	0	0	1	0	0

functional model perspective, analyzing user-system interactions in such complex systems is not a simple task. It is essential to establish standard associations that can be used to mitigate such discrepancies while building the set of matrices. This paper expands on the FHEDM by using association rules to automate the identification of user tasks from a functional model, and enhance our perspective of user-system interactions and failure modes associated with such user interactions.

3 METHODOLOGY

The objective of this work is to data-mine the Design Repository to identify *component*, *function-flow*, and *users tasks* associations. These associations can be used to distinguish user interactions when designing a new product. Mining the Design Repository with *components functions-flows* and *users' tasks* relationships has the potential to support designers by improving design knowledge and reinforcing design decisions regarding human factors early in the design process. We achieved the *component*, *function-flow* and *users tasks* relationships by implementing an *Apriori* algorithm into the current product data in the Design Repository. Figure 5 describes step by step the methodology used in this research. We selected the *Apriori* algorithm because it represents an efficient approach to determine association rules. The *Apriori* algorithm uses the measures of association to limit the number of itemsets that are explored based on a minimum threshold for support and confidence, thus decreasing computational complexity.

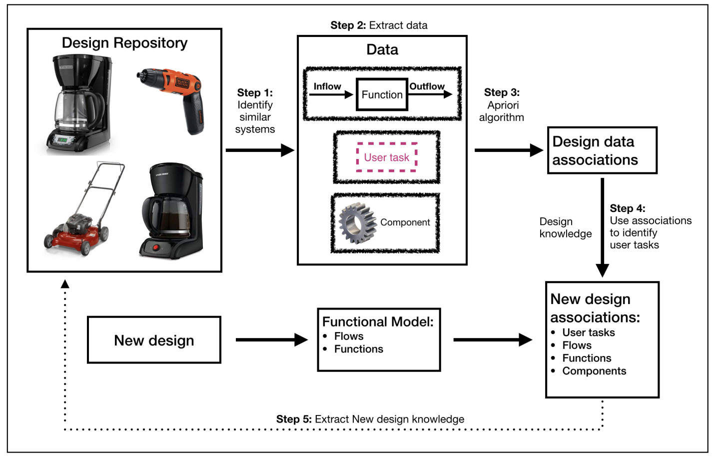

FIGURE 5: Methodology

Step 1. From the Design repository, we selected a set of products that share some similar functionality. For this work, we want to use a similar set of data to understand the resulting association rules and identify possible anomalies in the data set. Additionally, using products that share similar functionality allow us to identify important patterns in the data. Future work will extract dataset of diverse products from the Design Repository. For this study, we selected six different coffee makers.

Step 2. We proceeded to extract data about the *components*, *functions-flows*, and *user tasks* for each coffee maker from the Design Repository.

Step 3. We applied machine learning using an *Apriori* algorithm to the extracted data to calculate the probabilities of associations between *components-functions-flows* and *user tasks*. The outputs of the algorithm are a list of *functions-flows*, and *user tasks* associated with an specific *component*, including the three measures of association: **Support**, **Confidence**, and **Lift** (previously defined in the literature review section).

Step 4. The results were used to define association rules between the *functions-flows*, and *user tasks*, which then can be used as inputs in a new functional model analysis to identify possible user tasks. In this work, we utilize the results from associations to determine the *user tasks* for a functional model of an electric kettle. To verify the approach, we compare the relationships built by the authors using FHEDM with the relationships generated from the associations (*Apriori* algorithm).

Step 5. From the results obtained from the associations of the new system, we learned new design information which can be used to expand the data within the Design Repository. In this work, we are not adding new data to the Repository. We are examining the results to evaluate the capability of the approach to establish the associations. Future work will explore the application of association rules to expand and refine the design data in the Design Repository.

4 CASE STUDY

As proof of concept, we are first applying the proposed methodology to a group of consumer products that have a relatively small number of *functions* and *flows*. We are defining product complexity within the Design Repository in terms of the number of *functions* and *flows* present in a system. Applying the method in a smaller dataset would allow us to identify potential errors and pitfalls in the results. If proven right, then we can scale up to analyze more complex datasets from the Repository.

We applied the methodology to a set of six coffee makers extracted from the Design Repository. The coffee maker datasets have 35 unique components with 393 total combinations of *components-functions-flows*, and *user tasks*, 152 of which are unique. The *Apriori* algorithm uses the measures of association to limit the number of itemsets that are explored based on a minimum threshold for **Support** and **Confidence**; thus, decreasing computational complexity, which is an efficient approach to find association rules from large datasets. The algorithm executes in Python using the library called PyFIM [25]. The Python *Apriori* algorithm requires an input of data as well as a declaration of minimum thresholds for the three measures of association: *Support*, *Confidence*, and *Lift*. Initially, these thresholds are set low in order to maximize the data returned to begin learning the relationships between *components-functions-flows* and *users tasks*. For this work, the minimum thresholds were set to *Confidence =0.05*, *Support = 0.001* and *Lift = 1*. **Lift** values greater than 1 indicates the presence of an association rule. High values of **Lift** indicate stronger relationships between the items.

We evaluate the associations of *components-functions-flows* and *user tasks* relationships by comparing the results of the *Apriori* algorithm with the relationships built by the authors using FHEDM for a functional model of an electric kettle. The electric kettle was selected for analysis as the operation and control of a kettle have similar user interactions than the operations of a coffee maker. By comparing these similar products, we can find meaningful connections between *components-functions-flows* and *user tasks* associations through repetition.

Additionally, we expect potential problems, as well as meaningful correlations, can be identified while using a smaller set of data before applying the methodology to a larger and more complex set of data. The functional model for the electric kettle is presented in Fig. 6 and the results of the user interactions using FHEDM are presented in Tab. 4.

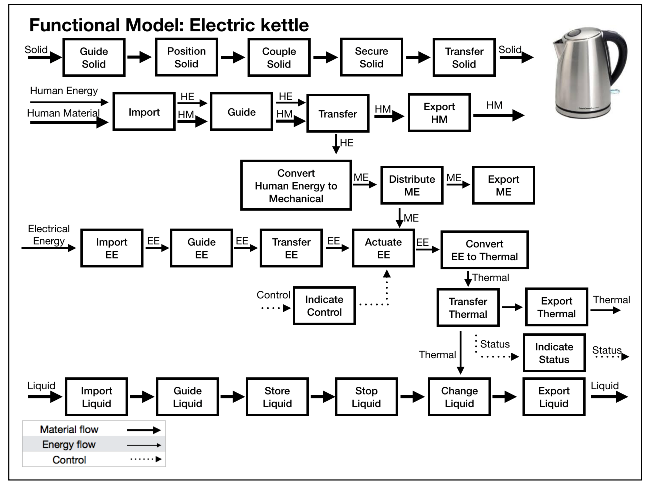

FIGURE 6: Functional Model Electric kettle

5 RESULTS & DISCUSSION

5.1 Apriori algorithm

The resulting associations from the *Apriori* algorithm for the coffee maker set are presented in Appendix A Tab. 6. From these set of preliminary results, we can identify with certainty associations between *user tasks* with a specific set of *functions-flows*, and *components*. Using the combination of high certainty metrics, we can categorize some of the *components* and *functions-flows* combinations to have a specific *user tasks*. The dataset extracted from the coffee maker set, groups each association using a **Head** and a **Body**.

- The **Head** is a group of items within a *flow-function-flow* and *component* combination that governs the likelihood of a given **Body**.
- The **Body** is a single *user task* that could be result given a probability defined by what items are in the *flow-function-flow & component* combination.

The significance of the observed associations can be assessed with the values of **Support** and **Confidence** and **Lift**. To describe what these values mean we took one result from Appendix A Tab. 6 for the *inflow-function-outflow & component:* "human energy (HE)-import-human energy (HE)-electric & switch" and the *user task:* "grasping"

HE-import-HE & electric switch ⇒Grasping
[Confidence: 20.00%, Support: 0.80%, Lift: 8.23]

Support is the percentage of itemsets in the dataset that contain both the *user task* "grasping" and the *flow-function & component* set "human energy-import-human energy & electric switch" together. Only 0.80% of the coffee makers data had these itemset together.

Confidence is the percentage of itemsets in the dataset, containing the *user task* "grasping", that also contains the *flow-*

TABLE 4: FHEDM user tasks for electric kettle

Electric Kettle			
Inflow	**Function**	**Outflow**	**User tasks**
solid	guide	solid	grasping, carrying in the hands
solid	position	solid	manipulating
solid	couple	solid	manipulating
solid	secure	solid	manipulating
solid	transfer	solid	marrying in the hands , releasing
human energy	import	human energy	reaching
human energy	guide	human energy	grasping, carrying in the hands
human energy	transfer	human energy	pushing, pulling, turning, lifting
human energy	convert	mechanical	pushing, pulling, turning, lifting
human material	import	human material	reaching
human material	guide	human material	grasping, carrying in the hands
human material	transfer	human material	pushing, pulling, turning, lifting
human material	export	human material	releasing
mechanical	distribute	mechanical	none
mechanical	export	mechanical	none
electrical	import	electrical	none
electrical	guide	electrical	none
electrical	transfer	electrical	none
electrical	actuate	electrical	manipulating, pushing, releasing
electrical	convert	thermal	none
thermal	transfer	thermal	none
thermal	export	thermal	none
control	indicate	control	watching, listening
status	indicate	status	watching, listening
liquid	import	liquid	manipulating
liquid	guide	liquid	carrying in the hands
liquid	store	liquid	none
liquid	stop	liquid	none
liquid	change	liquid	none
liquid	export	liquid	manipulating

function & component set "human energy-import-human energy & electric switch". For example, the probability of having the *user task* "grasping", given that "human energy-import-human energy" (*flow-function-flow*), an electric switch (*component*) is already in the coffee makers data (20% of all those who select "human energy-import-human energy & electric switch", also include "grasping".)

From the functional models of coffee makers present in the Design Repository, only 0.8% have the itemset: *Grasping→ human energy-import-human energy-electric switch*.

However, given the *flow-function-flow-component* set "human energy-import-human energy-electric switch", it is somewhat likely (20%) that the *user task* "grasping" will be selected. This demonstrates that if we have the functional model with the *flow-function-flow* "human energy-import-human energy" and the *component* "electric switch", there is a probability a user might not need to "grasp" the electric switch.

Lift is the **Support** of the *flow-function-flow & component* with the *user task* itemset divided by the product of the **Support** of the *flow-function-flow & component* and the *Support* of *user task*. A *Lift* value garter than "1" indicates that the *flow-function-flow & component* is likely to be associated with the *user task*. A *Lift* value of lower than "1" indicates that the flow-function-flow-component are unlikely to be associated. Therefore, exists an association between:

HE-import-HE & electric switch ⇒Grasping

From the results presented in Table 6, we selected meaningful associations that have 100% **Confidence**, **Support** in the top half of all the recorded supports, and **Lift** over "1". This threshold is selected to reduce falsely linking a *component* to certain *user task*. In general, most *flow-function-flow & component* combinations on the list are not associated with *user tasks*. In addition, there are *components* with multiple *user tasks* that appear based on the *flow-function-flow* combination. These are all listed as we do not have enough data to determine which *user tasks* is the most accurate. For example, from our results the item set *flow-function-flow & component*: "human energy-convert-status & handle" is associated with the *user tasks* "listening" and "watching". If the selected *component* ("electric switch") does not use any auditory signal to describe the status of the switch, the *user task* "listening" would not be present for this particular set of *flow-function-flow*. Table 6 is a predecessor to fully automating identifying how humans interact with products. Until more information is available, designers will need to use classical methods to relate *components* with *user tasks*. Unique *flow-function-flow & component* combinations will require designer cognition to inform *user tasks* as there is not an appropriate amount of data to confidently support data-mined associations.

5.2 Associations for the Electric Kettle Model

Next, using the resulting associations gathered from the coffee maker dataset, we proceed to use such associations to recognize possible *user tasks* present in the functional model of a new product. To evaluate this method, we use the associations presented in Table 6 (Appendix A) to distinguish *user tasks* for the functional model of an electric kettle shown in Figure 6.

We compared the *functions, flows* and *user interaction*s built by the authors using the FHEDM (Table 4) with the associations derived from the data mining results for the electric kettle. Table 5 shows the comparison of the results. The left side of the table present the Associations built by the authors using the FHEDM, while the right side of the table presents the Associations derived from the *Apriori* algorithm. We have included the Lift value to

TABLE 5: Association results for the electric kettle

Identical Associations

Associations built by the author (FHEDM)		Association Rules derived by *Apriori* Algorithm			
Inflow - Function - Outflow	**User task**	**User task**	**Component**	**Inflow - Function - Outflow**	**Lift**
human energy - import - human energy	reaching	reaching	housing	human energy - import - human energy	16.56
human material - guide - human material	grasping - carrying in the hands	carrying in the hand	handle	human material - guide - human material	12.42
electrical - import - electrical	none	none	electric cord	electrical - import - electrical	1.23
electrical - convert - thermal	none	none	heating element	electrical - convert - thermal	1.23
thermal - transfer - thermal	none	none	heating element	thermal - transfer - thermal	1.23

Similar Associations

Associations built by the author (FHEDM)		Association Rules derived by *Apriori* Algorithm			
Inflow - Function - Outflow	**User task**	**User task**	**Component**	**Inflow - Function - Outflow**	**Lift**
status - indicate - status	watching - listening	other purposeful sensing	lever	status - sense - status	99.40
human material - transfer - human material	pushing - pulling - turning - lifting	lifting	handle	human material - guide - human material	62.12
human energy - transfer - human energy	grasping - pushing - pulling - turning - lifting	pushing	electric switch	human energy - convert - control	41.42
control - indicate - control	watching - listening	manipulating	electric switch	control - actuate - control	27.62
human material - export - human material	releasing	manipulating	handle	human material - guide - human material	20.70
human energy - guide - human energy	grasping - carrying in the hands	grasping	system	human energy - contain - human energy	13.80
human material - import - human material	reaching	reaching	housing	human energy - import - human energy	16.56
mechanical - distribute - mechanical	none	none	electric cord	electrical - supply - electrical	1.23
mechanical - export - mechanical	none	none	electric switch	status - export - status	1.23
electrical - guide - electrical	none	none	electric wire	electrical - supply - electrical	1.23
electrical - transfer - electrical	none	none	mechanical transformer	electrical - supply - electrical	1.23
thermal - export - thermal	none	none	support	thermal - transfer - thermal	1.23
liquid - change - liquid	none	none	heating element	solid-liquid - change - solid-liquid	1.23
liquid - store - liquid	none	none	reservoir	solid-liquid - store - solid-liquid	1.23

Distinct Associations

Associations built by the author (FHEDM)		Association Rules derived by *Apriori* Algorithm			
Inflow - Function - Outflow	**User task**	**User task**	**Component**	**Inflow - Function - Outflow**	**Lift**
solid - guide - solid	grasping - carrying in the hands	none	container	solid - guide - solid	1.23
solid - position - solid	manipulating	none	handle	solid - position - solid	1.23
solid - couple - solid	manipulating	none	heating element	solid - couple - solid	1.23
solid - secure - solid	manipulating	none	support	solid - secure - solid	1.23
solid - transfer - solid	carrying in the hands - releasing	none	handle	solid - guide - solid	1.23
human energy - convert - mechanical	pushing - pulling - turning - lifting	none	handle	human energy - convert - translational	1.23
electrical - actuate - electrical	manipulating - pushing - releasing	none	electric switch	electrical - actuate - electrical	1.23
liquid - import - liquid	manipulating	none	cover	solid-liquid - import - solid-liquid	1.23
liquid - guide - liquid	carrying in the hands	none	tube	solid-liquid - transfer - solid-liquid	1.23
liquid - stop - liquid	none	none	container	solid-liquid - actuate - solid-liquid	1.23
liquid - export - liquid	manipulating	none	cap	solid-liquid - transfer - solid-liquid	1.23

estimate the strength of the resulting association rule generated by the algorithm. The results are arranged into three categories **Identical Associations**, **Similar Associations**, and **Distinct Associations**.

The **Identical Associations** category groups the *flow-function-flow* and *user tasks* associations that are a perfect match between the associations built by the authors and the associations distinguished from coffee maker set. From the results, we only identify five *functions, flows* and *user taks* sets that are equal for the two groups. The resulting Associations are identical for both the authors and the *Apriori* algorithm. Nevertheless, only two of the association rules identified in this category have **Lift** values higher than 1.23.

The **Similar Associations** category groups the *function-flow* and *user task* associations that share affinities between the associations established by the authors and the associations derived from a coffee maker set. We use the *Apriori* algorithm with a dataset captured from functional models of distinct coffee makers. The *functions* and *flows* present in a coffee maker are slightly different and more complicated than the *functions* present in an electric kettle. Therefore, we do not expect to find identical associations. However, one can classify *functions* that aim to achieve an equivalent purpose. For example, the electric kettle has the set “human energy-transfer-human energy” which describes the user “grasping” the kettle to interact with it. In the coffee maker dataset, an equivalent function is the set “human energy-convert-control” which describes the user “pushing” the controls to interact with the coffee maker. The components present in the dataset support our judgments to make such similarities. For example, the electric kettle has the set “human material-export-human material” and “releasing”, which is similar to the set “human material-guide-human material”, “manipulating” with the component “handle” which describes the user “manipulating” the handle to guide the coffee maker. Additionally, in the Similar Association category, the *Apriori* algorithm defined strong Association Rules with significantly large **Lift** values for 7 of the itemsets.

The **Distinct Association's** category groups the *function-flow* and *user task* associations that have no similarities between the associations established by the authors and the associations derived from coffee maker dataset. In this category, we find *function* and *flow* combinations that are identical or similar between the two sets, although the *user tasks* for the set are not a match. These differences could be the result of the small overlap between *components* and *function-flows*. Like we explained before, even though a coffee maker shares similar functionality and user tasks with the electric kettle, they complete different distinct operations. For the last category, the resulting associations' rules have a **Lift** value close to the threshold value (**Lift** =1).

6 DISCUSSION

In this work, we used a set of coffee makers dataset from the Design Repository to determine associations between *components*, *functions*, *flows*, and *user tasks* using an *Apriori* algorithm. We evaluated the association rules generated from the dataset by identifying *user tasks* from a functional model of an electric kettle. We compared the associations extracted from the dataset against the associations defined by the authors using the Function Human Error Design Method (FHEDM).

The results verify the similarities of the associations between the dataset and the FHEDM. However, the limited size and scope of the dataset used during the initial exploration restricts the capability of identifying user tasks from more extensive and more complicated functional models. We will expand the dataset by incorporating a different set of products, which will increase the accuracy of the association rule learning.

Current design methodologies struggle while incorporating human factors during the early design stages. Designers can not correctly identify or asses the user-system interactions during the initial design stages. Failure modes caused by human-system interactions are not being identified. Identifying a set of possible user tasks from a functional model, have the potential of transforming the design process by consolidating human factors principles during the early design stages. Additionally, it can bring to light diverse design concepts that support user performance, comfort, and safety; while distinguishing failure modes caused by human-system interactions are not being identified.

Our results confirmed that association rules can be used to identify *user tasks* using the *functions-flows* presented in a functional model of a product. We observed that the accuracy of such associations learned depends on the quality and size of the dataset. Even though the associations defined from the dataset matched in 100% with the associations defined by the authors, we were able to find strong similarities for the *functions*, *flows*, and*user tasks*, which confirms the capability of our approach.

From the results, we identified sets of data that need to be revised from the Design Repository. For some combinations of the *flows* and *functions*, the *user tasks* defined was not adequately determined. By incorporating the data of the *components* to the established associations, we can appropriately choose the *user tasks* required to operate the component and complete the desired function.

This research provides the basis for increasing design knowledge into the Design Repository by first incorporating the data regarding the physical user interactions and failure modes associated with such interactions. Second by building and refining the association rules between *functions*, *flows*, *user tasks*, and *components*. Third, by enhancing auxiliary design knowledge and decision support based on the physical user tasks required to perform the product function. Furthermore, this work contributes towards developing a design tool capable of automating functional modeling construction, understanding user interactions, identifying potential design deficiencies caused by poor user considerations, and failure modes caused by a component malfunction. This research proved that this scenario is possible through the extraction and generation of design association rules from a rich and diverse set of data.

7 FUTURE WORK

This work is part of the research done by Design Laboratory at Oregon State University (OSU) towards the development of an automated functional model generator tool. Such tool will help designers to standardize the language and syntax used in functional models, enabling the design of new products based on components, the functionality of the components, and by incorporating human factor design principles early in the design process.

The presented results confirm that user interactions can be identified from a functional model. Future work will assess failure modes associated with such user interactions and evaluate the usability, performance, and safety of the user while interacting with the product. Additionally, our results can be used as a developing point towards using grammar rules to connect components to functions, flows and user tasks.

We will apply the *Apriori* algorithm to a larger dataset that includes a diverse set of products. This input will further increase the size and quality of the data and the resulting associations.

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Appendix A: Apriori Algorithm Results Coffee Maker set

TABLE 6: Coffee maker set from Design Repository Associations

Coffee maker set from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
lifting	HM guide HM	handle	12.50	0.20	62.12
listening	HE convert SS	circuit board	33.33	0.60	41.41
watching	HE convert SS	circuit board	33.33	0.60	41.41
listening	HE convert SS	electric switch	33.33	0.20	41.41
watching	HE convert SS	electric switch	33.33	0.20	41.41
manipulating	HE convert control	electric switch	25.00	0.20	41.41
pulling	HE convert control	electric switch	25.00	0.20	41.41
pushing	HE convert control	electric switch	25.00	0.20	41.41
other purposeful sensing	HE convert SS	circuit board	33.33	0.60	33.13
other purposeful sensing	HE convert SS	electric switch	33.33	0.20	33.13
manipulating	control actuate control	electric switch	16.67	0.20	27.61
pulling	control actuate control	electric switch	16.67	0.20	27.61
pushing	control actuate control	electric switch	16.67	0.20	27.61
standing	HE contain HE	system	33.33	0.80	20.70
manipulating	HM guide HM	handle	12.50	0.20	20.70
pulling	HM guide HM	handle	12.50	0.20	20.70
pushing	HM guide HM	handle	12.50	0.20	20.70
carrying in the hands and handling objects	HM contain HM	system	20.00	0.80	19.88
picking up	HE import HE	electric switch	20.00	0.80	16.56
picking up	HE import HE	visual indicator	20.00	0.20	16.56
reaching	HE import HE	visual indicator	20.00	0.20	16.56
picking up	HE import HE	housing	20.00	0.20	16.56
reaching	HE import HE	housing	20.00	0.20	16.56
grasping	HE contain HE	system	33.33	0.80	13.80
visual indicator	transferring oneself	HE import HE	16.67	0.20	13.80
reaching	HE import HE	visual indicator	16.67	0.20	13.80
picking up	HE import HE	visual indicator	16.67	0.20	13.80
grasping	HE import HE	visual indicator	16.67	0.20	13.80
changing basic body position	HE import HE	visual indicator	16.67	0.20	13.80
standing	HM contain HM	system	20.00	0.80	12.42
carrying in the hands and handling objects	HM guide HM	handle	12.50	0.20	12.42
changing basic body position	HM contain HM	system	20.00	0.80	9.03
transferring oneself	HM contain HM	system	20.00	0.80	9.03
changing basic body position	HE import HE	electric switch	20.00	0.80	9.03
transferring oneself	HE import HE	electric switch	20.00	0.80	9.03
changing basic body position	HE import HE	visual indicator	20.00	0.20	9.03
transferring oneself	HE import HE	visual indicator	20.00	0.20	9.03
changing basic body position	HE import HE	housing	20.00	0.20	9.03
transferring oneself	HE import HE	housing	20.00	0.20	9.03
grasping	HE import HE	electric switch	20.00	0.80	8.28
grasping	HE import HE	visual indicator	20.00	0.20	8.28
grasping	HE import HE	housing	20.00	0.20	8.28
changing basic body position	control actuate control	electric switch	16.67	0.20	7.53
grasping	control actuate control	electric switch	16.67	0.20	6.90
transferring oneself	HM guide HM	handle	12.50	0.20	5.64
grasping	HM guide HM	handle	12.50	0.20	5.17
none	solid secure solid	visual indicator	2.04	0.20	1.69
none	solid couple solid	screw	100.00	8.45	1.23

Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)

Electrical Energy (EE) - Tactile Status (TS) - Visual Status (VS)

Continued on next page

Table 6 – continued from previous page

Coffee maker set from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
none	solid-liquid transfer solid-liquid	tube	100.00	3.02	1.23
none	solid position solid	seal	100.00	2.41	1.23
none	solid couple solid	housing	100.00	2.01	1.23
none	solid secure solid	tube	100.00	1.61	1.23
none	solid guide solid	cover	100.00	1.61	1.23
none	solid position solid	cover	100.00	1.41	1.23
none	solid position solid	container	100.00	1.41	1.23
none	solid position solid	tube	100.00	1.21	1.23
none	solid guide solid	tube	100.00	1.21	1.23
none	solid secure solid	seal	100.00	1.21	1.23
none	solid-liquid import solid-liquid	cover	100.00	1.01	1.23
none	solid-liquid change solid-liquid	heating element	100.00	1.01	1.23
none	solid guide solid	seal	100.00	1.01	1.23
none	solid secure solid	housing	100.00	1.01	1.23
none	solid couple solid	cover	100.00	1.01	1.23
none	solid couple solid	bracket	100.00	1.01	1.23
none	thermal transfer thermal	heating element	100.00	0.80	1.23
none	thermal contain thermal	system	100.00	0.80	1.23
none	solid-liquid store solid-liquid	tube	100.00	0.80	1.23
none	solid-liquid store solid-liquid	housing	100.00	0.80	1.23
none	solid-liquid separate solid-liquid	container	100.00	0.80	1.23
none	solid-liquid mix solid-liquid	container	100.00	0.80	1.23
none	solid-liquid actuate solid-liquid	cover	100.00	0.80	1.23
none	solid store solid	container	100.00	0.80	1.23
none	solid export solid	container	100.00	0.80	1.23
none	solid position solid	reservoir	100.00	0.80	1.23
none	liquid contain liquid	system	100.00	0.80	1.23
none	solid guide solid	housing	100.00	0.80	1.23
none	solid couple solid	handle	100.00	0.80	1.23
none	solid guide solid	handle	100.00	0.80	1.23
none	EE import EE	electric cord	100.00	0.80	1.23
none	EE convert thermal	heating element	100.00	0.80	1.23
none	EE contain EE	system	100.00	0.80	1.23
one	solid couple solid	clamp	100.00	0.80	1.23
none	solid position solid	bracket	100.00	0.80	1.23
none	solid couple solid	tube	100.00	0.60	1.23
none	solid position solid	thermal plate	100.00	0.60	1.23
none	solid couple solid	tube	100.00	0.60	1.23
none	solid position solid	thermal plate	100.00	0.60	1.23
none	thermal distribute thermal	container	100.00	0.60	1.23
none	solid position solid	support	100.00	0.60	1.23
none	solid secure solid	support	100.00	0.60	1.23
none	SS store SS	circuit board	100.00	0.60	1.23
none	solid position solid	spring	100.00	0.60	1.23
none	solid-liquid store solid-liquid	container	100.00	0.60	1.23
none	solid-liquid store solid-liquid	reservoir	100.00	0.60	1.23
none	solid import solid	cover	100.00	0.60	1.23
none	solid export solid	cover	100.00	0.60	1.23
none	solid position solid	housing	100.00	0.60	1.23
none	solid couple solid	heating element	100.00	0.60	1.23
none	solid position solid	heating element	100.00	0.60	1.23
none	solid position solid	handle	100.00	0.60	1.23
none	solid position solid	heating element	100.00	0.60	1.23
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Electrical Energy (EE) - Tactile Status (TS) - Visual Status (VS)					

Continued on next page

Table 6 – continued from previous page

Coffee maker set from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
none	solid position solid	handle	100.00	0.60	1.23
none	EE supply EE	electric cord	100.00	0.60	1.23
none	solid secure solid	electric wire	100.00	0.60	1.23
none	EE supply EE	electric wire	100.00	0.60	1.23
none	container	solid guide solid	100.00	0.60	1.23
none	solid position solid	cap	100.00	0.60	1.23
none	solid secure solid	cap	100.00	0.60	1.23
none	solid couple solid	belt	100.00	0.60	1.23
none	solid position solid	belt	100.00	0.60	1.23
none	solid position solid	valve	100.00	0.40	1.23
none	solid-liquid actuate solid-liquid	valve	100.00	0.40	1.23
none	thermal transfer thermal	thermal plate	100.00	0.40	1.23
none	thermal distribute thermal	reservoir	100.00	0.40	1.23
none	solid couple solid	support	100.00	0.40	1.23
none	SS transfer SS	lever	100.00	0.40	1.23
none	solid-liquid actuate solid-liquid	seal	100.00	0.40	1.23
none	solid secure solid	reservoir	100.00	0.40	1.23
none	solid guide solid	reservoir	100.00	0.40	1.23
none	solid secure solid	heating element	100.00	0.40	1.23
none	solid couple solid	guiders	100.00	0.40	1.23
none	solid position solid	guiders	100.00	0.40	1.23
none	solid secure solid	guiders	100.00	0.40	1.23
none	EE actuate EE	electric switch	100.00	0.40	1.23
none	EE actuate EE	circuit board	100.00	0.40	1.23
none	solid secure solid	electric switch	100.00	0.40	1.23
none	solid secure solid	electric cord	100.00	0.40	1.23
none	solid secure solid	clamp	100.00	0.40	1.23
none	solid couple solid	circuit board	100.00	0.40	1.23
none	solid couple solid	cap	100.00	0.40	1.23
none	solid guide solid	bracket	100.00	0.40	1.23
none	solid secure solid	visual indicator	100.00	0.20	1.23
none	solid secure solid	valve	100.00	0.20	1.23
none	solid guide solid	valve	100.00	0.20	1.23
none	solid couple solid	unclassified	100.00	0.20	1.23
none	solid secure solid	unclassified	100.00	0.20	1.23
none	solid-liquid import solid-liquid	unclassified	100.00	0.20	1.23
none	thermal transfer thermal	cover	100.00	0.20	1.23
none	thermal transfer thermal	support	100.00	0.20	1.23
none	solid guide solid	thermal plate	100.00	0.20	1.23
none	thermal distribute thermal	thermal plate	100.00	0.20	1.23
none	solid position solid	thermal insulator	100.00	0.20	1.23
none	solid guide solid	thermal insulator	100.00	0.20	1.23
none	thermal distribute thermal	cover	100.00	0.20	1.23
none	thermal distribute thermal	support	100.00	0.20	1.23
none	SS export SS	electric switch	100.00	0.20	1.23
none	SS convert EE	circuit board	100.00	0.20	1.23
none	SS actuate SS	seal	100.00	0.20	1.23
none	SS actuate SS	circuit board	100.00	0.20	1.23
none	solid guide solid	spring	100.00	0.20	1.23
none	solid-liquid-gas actuate solid-liquid-gas	seal	100.00	0.20	1.23
none	solid-liquid separate solid	container	100.00	0.20	1.23
none	solid-liquid separate solid-liquid	reservoir	100.00	0.20	1.23
none	solid-liquid mix solid-liquid	reservoir	100.00	0.20	1.23
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Electrical Energy (EE) - Tactile Status (TS) - Visual Status (VS)					

Continued on next page

Table 6 – continued from previous page

Coffee maker set from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
none	solid-liquid contain solid-liquid	cover	100.00	0.20	1.23
none	solid-liquid actuate solid-liquid	container	100.00	0.20	1.23
none	solid store solid	reservoir	100.00	0.20	1.23
none	solid mix solid-liquid	container	100.00	0.20	1.23
none	solid import solid	container	100.00	0.20	1.23
none	solid import solid	housing	100.00	0.20	1.23
none	solid export solid	housing	100.00	0.20	1.23
none	solid export solid	reservoir	100.00	0.20	1.23
none	solid couple liquid	screw	100.00	0.20	1.23
none	solid couple solid	reservoir	100.00	0.20	1.23
none	object guide object	handle	100.00	0.20	1.23
none	solid couple solid	nut-bolt	100.00	0.20	1.23
none	solid guide solid	nozzle	100.00	0.20	1.23
none	solid-liquid transfer solid-liquid	nozzle	100.00	0.20	1.23
none	solid couple solid	mechanical transformer	100.00	0.20	1.23
none	solid secure solid	mechanical transformer	100.00	0.20	1.23
none	EE supply EE	mechanical transformer	100.00	0.20	1.23
none	solid-liquid condition solid-liquid	material filter	100.00	0.20	1.23
none	HE convert translational		100.00	0.20	1.23
none	HE convert translational	handle	100.00	0.20	1.23
none	solid secure solid	handle	100.00	0.20	1.23
none	solid guide solid	guiders	100.00	0.20	1.23
none	EE supply EE	heating element	100.00	0.20	1.23
none	EE import EE	electric wire	100.00	0.20	1.23
none	EE actuate EE	heating element	100.00	0.20	1.23
none	solid position solid	electric wire	100.00	0.20	1.23
none	solid couple solid	electric switch	100.00	0.20	1.23
none	solid position solid	electric cord	100.00	0.20	1.23
none	solid secure solid	cover	100.00	0.20	1.23
none	solid position solid	clamp	100.00	0.20	1.23
none	solid position solid	circuit board	100.00	0.20	1.23
none	solid secure solid	circuit board	100.00	0.20	1.23
none	solid guide solid	cap	100.00	0.20	1.23
none	solid-liquid transfer solid-liquid	cap	100.00	0.20	1.23
none	solid secure solid	bracket	100.00	0.20	1.23
none	solid secure solid	belt	100.00	0.20	1.23