Uncovering Human Errors Associated with System-User Interactions Using Functional Modeling

Nicolás F. Soria Zurita*
Engineering Design
The Pennsylvania State University
University Park, PA, USA
Email: nicosoria@psu.edu
Colegio de Ciencias e Ingeniería
Universidad San Francisco de Quito
Quito, Ecuador

Melissa Anne Tensa, Vincenzo Ferrero,
School of Mechanical, Industrial
and Manufacturing Engineering
Oregon State University
Corvallis, Oregon, 97331
Email: tensam@oregonstate.edu
Email: ferrerov@oregonstate.edu

Robert B. Stone, Bryony DuPont
School of Mechanical, Industrial
and Manufacturing Engineering
Oregon State University
Corvallis, Oregon, 97331
Email: rob.stone@oregonstate.edu
Email: bryony.dupont@oregonstate.edu

H. Onan Demirel, and Irem Y. Tumer
School of Mechanical, Industrial
and Manufacturing Engineering
Oregon State University
Corvallis, Oregon, 97331
Email: onan.demirel@oregonstate.edu
Email: irem.tumer@oregonstate.edu

*Address all correspondence to this author.

ABSTRACT

Designers should adequately develop user considerations such as usability, safety, and comfort during the design process of new systems. Nevertheless, incorporating human factors engineering principles during early design phases is not simple. The objective of this work is to assist designers in implementing human factors engineering principles during early design phases using a functional model framework. This effort expands our previous work on automating the Function-Human Error Design Method (FHEDM) implementation. In this work, we use data mining techniques in a design repository to explore the construction of association rules between components, functions, flows, and user interactions. Such association rules can support designers assessing user-system interactions during the early design stages. To validate this approach, we compare the associations generated by expert designers using the FHEDM while designing a new product to those generated by an algorithm using the repository data. The results show notable similarities between the associations extracted by the algorithm and the associations identified by designers. Thus, the overall results show that association rules extracted from a rich dataset can be used to distinguish user-product interactions, demonstrating the potential of automating the identification of user-product interactions from a functional model.

1 INTRODUCTION

Today's designers are challenged with creating and innovating engineering systems that require more complex problem-solving approaches. In addition, the increasing complexity in consumer products and engineered systems raises the need to support engineers with design knowledge beyond cognitive memory. Product design is traditionally concentrated 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. Generally, Human Factors Engineering (HFE) methods are treated in isolation from the design process, and they are often incorporated after a design has been defined. At this stage, assessing the final user interacting with the design requires constructing full-scale physical or virtual prototypes and applying human-subject data collection. Applying HFE after the system has been designed is costly and time-consuming, and has limitations [1–5]. 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 [6]. Additionally, it can reduce expenses by decreasing the need for developing physical prototypes of the system for val-

idation [7, 8]. Design approaches that include user considerations during the early design stages can significantly enhance the user's safety and comfort [7–9]. As a result, recent research efforts are exploring the human error and component failure assessment methods, including Systematic Human Error Reduction and Prediction Approach (SHERPA) [10, 11], Function Human Error Design Method (FHEDM) [12], and Human Error and Functional Failure Reasoning (HEFFR) [13, 14].

The functional model with the Functional Basis is a well-known design methodology that supports designers to form a design concept during the early design stages by graphically describing flows and functions [15–17]. This method is popular because it allows designers to use a standardized language to describe flows, functions, and components [15, 16, 18]. Nevertheless, designers' functional models of the same concept can widely vary [18, 19]. Additionally, it is not very easy to create a functional model of systems with a considerably large number of functions and flows. For that reason, recent work explores design methods that automate the construction of functional models [20–25].

1.1 Specific Contributions

This research aims to support designers by introducing auxiliary design knowledge regarding HFE during design realization. In previous work, we introduced the Function-Human Error Design Method (FHEDM), which can identify physical user-system interactions and distinguish possible failure modes caused by erroneous system-user interactions during the early design stages using a Functional Basis framework [12, 22, 26]. This work extends the FHEDM by utilizing association rules extracted from an existing Design Repository to understand the relationships between functions, flows, and physical user interactions. An association rule learning approach is implemented using an *Apriori* algorithm to search design data and determine the probabilities of relationships between user tasks, components, functions, and flows. These associations can then be used to identify user interactions errors from a functional model, thus facilitating designers to make informed decisions to improve user performance, comfort, and safety.

The remainder of this paper is organized as follows. First, 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 in Section 3. Next, Section 4 presents the demonstration study used in this work, and Section 5 compares the results. Finally, a discussion of our work followed by conclusions and future work are provided in Sections 6, and 7.

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 the limitations of the methodology.

2.1 Design Repositories

Design repositories advance the use of design data to develop and expand design methodologies and knowledge [27–30]. Traditional design repositories collect data sets of product information such as bills of materials, cost data, CAD models, manufacturing processes, functional information, assembly data, and other DfX-relevant data. In addition, research efforts and industry applications have influenced the development of standardizing product data schemas [31, 32] and enabled the creation of extensively peer-reviewed design repositories [33–35]. Design repositories are still under development [21, 26, 28–30], and their impact on data-driven design processes can be valuable during the concept generation phase. For example, repositories featuring the collection of design information from a large set of products provide the seed for predictive models to estimate downstream impacts earlier in the design process [17, 36–38]. Design repositories are more useful than design databases, because they contain more comprehensive information, and provide a reliable mechanism for gathering, recording, and storing data [17, 24, 30, 39–41]. Recent efforts have focused on developing tools and design methodologies for automated concept generation [21,24,25,42–44] while examining environmental and social sustainability factors [29,35,45].This research argues that identifying association rules between physical user interactions and product functions from design repositories can improve the design process by introducing user performance, safety, and comfort during early design stages [12, 26].

In this work, we use functional model data stored in the Design Repository[1], hosted by the Design Engineering Lab at Oregon State University. The Design Repository contains information for over 130 consumer based electro-mechanical products at various levels of abstraction with over 5000 unique components [17, 31, 36, 39–41, 46]. Product information is stored and classified in categories, providing engineers and researchers with innovative ways to approach design by enabling 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 by the eleven categories containing

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

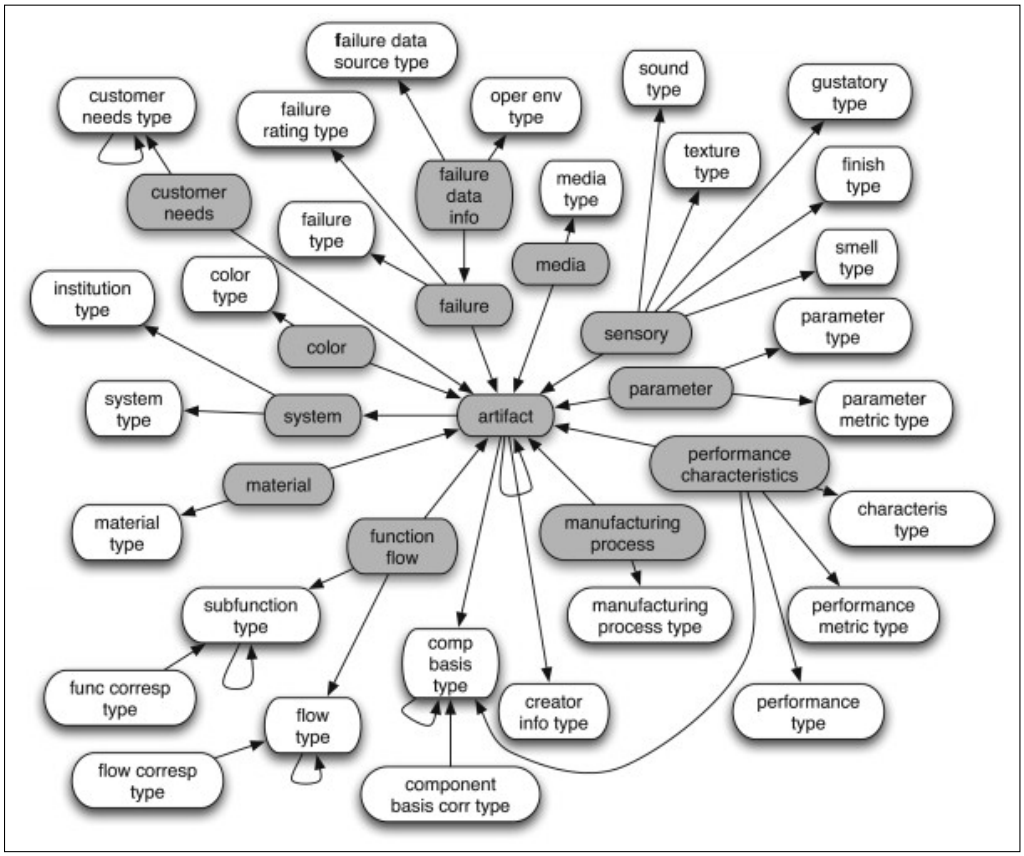

Fig. 1. Graphical representation of the Design Repository data schema [31]

tables pointing directly to the central component. Each product is divided into seven main categories of design information: artifact, function, failure, physical, performance, sensory and media-related information types [17, 21]. Various iterations of the Repository have refined the classification of the components and their functions to follow a standardized taxonomy [17, 24, 30, 35, 36, 39, 40]. In addition, recent research efforts have expanded and developed categories for sustainable design [23, 35] and HFE efforts [22, 26]. This work expands the Design Repository by developing a framework for extracting information and insights from product data (functions, flows, and components) and their relationships with the User Interactions. We used the functional model and functional basis [15, 16, 19, 47–49], the component basis [39], and Actionfunction diagrams [12, 26, 50–53] as the standardized design language. The Functional Basis is a standardized design vocabulary that uses a verb-object (function-flow pair) format to describe the different *functions* and *flows* working together within the functional model of a product or system [15, 16, 47]. Together, the functional modeling and the Functional Basis standardize a design language that uses a verb-object (*function-flow* pair) format to describe how the *functions* interact with the *flows* moving through a system. This

representation follows a flow diagram that illustrates the states and transitions of *flows* of energy, material, and information between the system *functions*. Actionfunction diagram relies upon the International Classification of Functioning, Disability, and Health (ICF), a standardized language to describe health and health-related states which was established by the World Health Organization [54]. Product functions are modeled using the Functional Basis, and user activities are represented using *ICF lexicon* [50, 54].

2.2 Association Rules and and Product Design

Data mining is the process of analyzing and studying information and patterns to discover knowledge about data [55, 56]. There have been extensive efforts exploring Association Rules to mine data from products in design research to identify the correlation between customer preferences and explore design space [57–59]. Moreover, recent work explores machine learning methods on repository data to advance product design processes through association rules [21–24]. Association rule learning is a rule-based machine learning method that searches information and determines the probabilities of relationships between the variables [21, 60–63]. 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 association rule mining to find non-obvious relationships between large datasets, mainly how one choice makes another choice more or less likely [64, 65]. In a canonical supermarket example, a customer buying hamburger buns is more likely to buy sliced cheese to prepare cheeseburgers, illustrating an association rule [66]. Like the example described above, we will use association rules within the Design Repository to identify correlations between *user interactions* and functional models of different products. Generating a mechanism to distinguish relationships between the product *functions*, *flows*, and *components* and the user (*user interactions*) just like the FHEDM [12, 22, 26].

One algorithm capable of generating association rules, learning over an itemset, and mining over databases is the *Apriori* algorithm [67]. The algorithm is well documented to help deal with large datasets and iteratively looks for frequent itemsets [62]. Applying the *Apriori* algorithm within the Design Repository can allow us to find correlations and establish relationships between the product (*functions, flows, and components*) and the user interacting with the product. The resulting associations can be used as a set of design principles that indicates the likelihood of certain user interactions with specific components or product functions, allowing designers to make informed design decisions during the design process.

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 <u>item</u> can be

a *user task*, a *function-flow*, and a *component* individually. In contrast, an <u>itemset</u> is the combination of the items like *component-function-flow* or *component-function-flow-user task* present in the data extracted from the Design Repository.

- Support indicates the prevalence of an item within all of the itemsets. In the cheeseburger example mentioned earlier, Support is the percentage of supermarket transactions containing hamburgers buns and sliced cheese. Mathematically, Support is represented as:

$$Support_{hamburgers \rightarrow cheese} = \frac{frequency(hamburgers\ buns,\ sliced\ cheese)}{Total_{transactions}} \tag{1}$$

- Confidence indicates the probability of two items appearing in the same item set. In the context of our application, Confidence is 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 containing 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:

$$Confidence_{hamburgers \rightarrow cheese} = \frac{frequency(hamburgers\ buns,\ sliced\ cheese)}{frequency(hamburgers\ buns)} \tag{2}$$

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

$$Lift_{hamburgers \rightarrow cheese} = \frac{Support_{hamburgers \rightarrow cheese}}{Support_{hamburgers} \times Support_{cheese}} \tag{3}$$

2.3 The Function-Human Error Design Method (FHEDM)

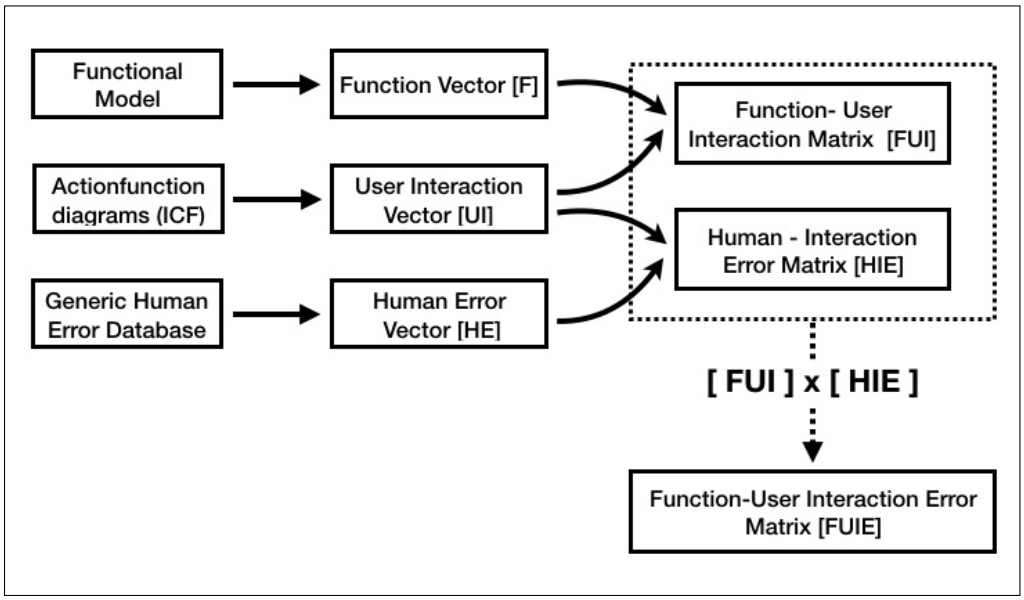

Fig. 2. Function Human Error Design Method (FHEDM) flow chart [12, 22, 26].

The Function-Human Error Design Method (FHEDM) aims to consolidate Human Factors Engineering principles using a functional-basis approach to understand physical user interaction during the early design stage [12, 22, 26]. FHEDM supports designers in identifying product functions that directly impact the user while distinguishing potential failure modes caused by user-product interactions during the conceptual design stage. 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].

– The Function-User Interaction matrix (FUI) is constructed using the functional model of the design and the Actionfunction diagram of the user interaction with the design. The FUI matrix 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 user's physical tasks needed to complete

to perform such function. The user interactions are described using the ICF lexicon [50–54, 68].

- The Human-Interaction Error Matrix [HIE] is constructed using the Actionfunction diagram of the user interaction with the design and the possible human errors associated with such user tasks. In addition, a generic human error database based on Human Factors Engineering literature was developed to support the FHEDM framework [12, 69–71]. The HIE matrix 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.
- The Function-User Interaction Error matrix [FUIE] is formed by the matrix multiplication of the FUI and HIE matrices (Equation 4). The resulting FUIE matrix highlights the number of occurrences for a particular human error while the user interacts with a given design function. Consequently, designers can identify sequences of functions with relevant human errors and incorporate HFE principles to improve the design.

$$[FUIE] = [FUI] \times [HIE] \tag{4}$$

In the current state of the FHEDM, the results are sensitive to the designers' decisions while manually developing the FUI and HIE matrices. Additionally, 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 manually using the expertise and experience of the designers with functional models and Actionfucntion diagrams. 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, making the construction of the FUI and HIE matrices more difficult. Analyzing user-system interactions in such complex systems is not a simple task from a functional model perspective. Therefore, it is essential to establish standard associations that can be used to lessen such discrepancies while building the set of matrices. This paper expands on the FHEDM by identifying association rules from the Design Repository data to automate the construction of the FUI matrix and enhance our perspective of user-system interactions and failure modes associated with such user interactions.

3 METHODOLOGY

This work aims to data-mine the Design Repository to identify association rules between *component, function-flow*, and *users tasks* to improve design knowledge and data-driven design decisions. This work defines data-driven design as methodologies for extracting insights and information from products data to improve design processes [72]. These associations can be used to distinguish potential difficulties with user interactions when designing a new product. Mining the Design Repository for relationships between components functions-flows and users' tasks can support designers by improving design knowledge and reinforcing design decisions regarding human factors early in the design process. We identified the component, function-flow, and users tasks relationships by implementing an *Apriori* algorithm into the current product data in the Design Repository. Figure 3 and the following bullet points describe step by step the mechanism used in this research to extract the data and identify the association rules between product functions-flows and users' tasks.

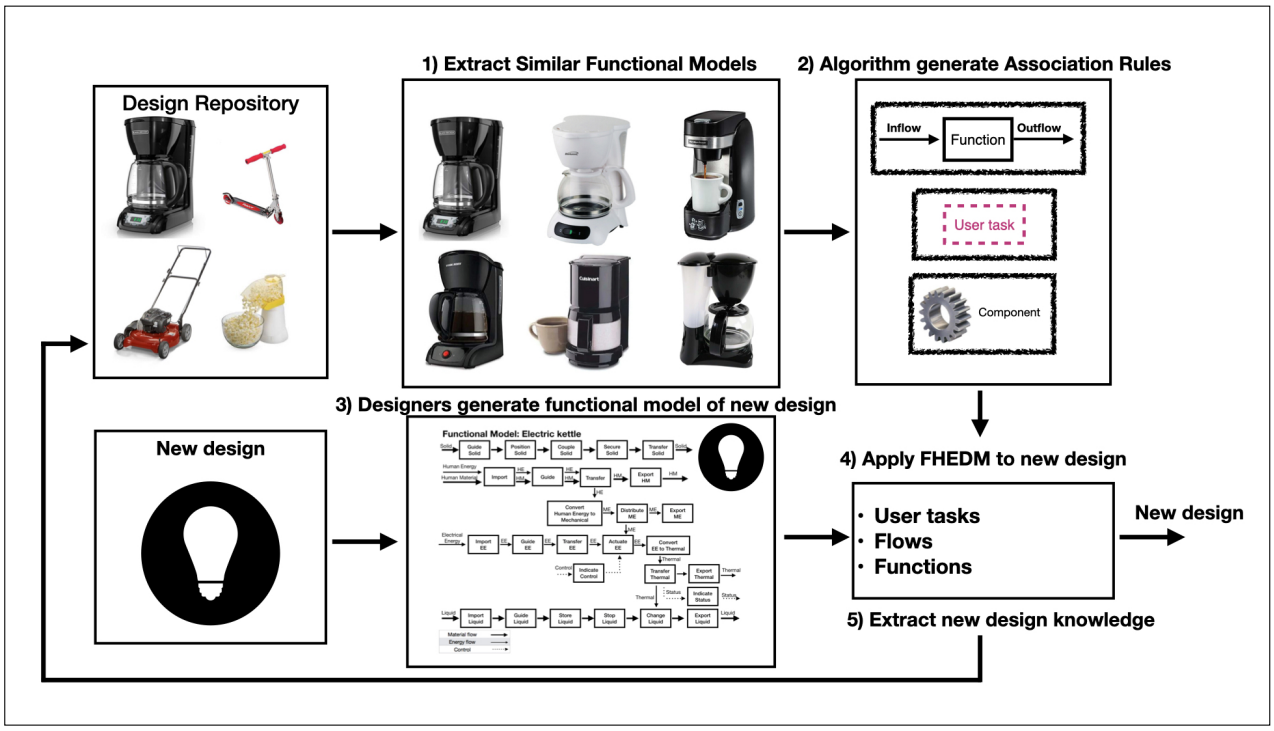

Fig. 3. Methodology flow chart. Step 1. Extract subset of Functional Models for a product from the Design Repository. Step 2. Apply Algorithm to generate Association Rules between components-functions-flows and user tasks for the subset of products. Step 3. Generate a functional model for new design. Step 4. Applied the association rules generated from the Apriori algorithm to automate the implementation of FHEDM to the new design. Step 5. Extract new design knowledge to refine the user-product interactions in the design and identify potential failure modes triggered by human error to expand the knowledge of the Design Repository.

- **Step 1. Extract Similar Functional Models**. We pull a subset of products that share similar functionality with the new product design from the Design Repository. To validate this approach, we want to use a similar subset of product data to understand the resulting association rules and identify possible anomalies in the data set. Additionally, using products that share similar functionality allows us to identify patterns in the data. Future work will explore extracting a large subset of different products from the Design Repository.
- **Step 2. Algorithm generates Association Rules.** We generate the association rules between components-functions-flows and user tasks for the subset of products extracted from the Design Repository. 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 algorithm's outputs are a list of functions-flows and user tasks associated with a specific component, including the three measures of association: Support (Eqn.1), Confidence (Eqn.2), and Lift (Eqn.3).
- **Step 3. Designers generate a functional model for the new design.** As part of the design process, designers generate a functional model of their design concept using the Functional Basis as the standardized design language.
- **Step 4. Designers applied FHEDM to the new design.** We applied the association rules generated from the Apriori algorithm to automate the implementation of FHEDM. Designers can use the identified associations to refine the user-product interactions in the design and recognize potential failure modes triggered by human error.
- **Step 5. Extract new design knowledge.** Finally, from the results determined in Step 4, new design information can be identified and used to extend the knowledge of the Design Repository. In this work, we are not adding new information to the Repository. Instead, we examine and compare the associations identified by designers and the algorithm to evaluate the Apriori algorithm's effectiveness in discovering associations. Future work will explore the use of association rules to expand and refine the data in the Design Repository.

4 DEMONSTRATION STUDY - DESIGN OF AN ELECTRIC KETTLE

Product complexity within the Design Repository is defined by the number of functions and flows present in a system. This work applies the proposed methodology to subgroups of consumer products with relatively similar complexity and functionality as a proof of concept. Using a smaller dataset can identify potential errors and pitfalls in the algorithm results. If proven correct, the methodology can be scaled up to analyze

more complex and different datasets from the Design Repository. For this work, the methodology described in Section 3 is applied to design a new electric kettle using a subset of coffeemakers extracted from the Design Repository to generate and validate association rules using the *Apriori* algorithm.

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. The algorithm executes in Python using the library called PyFIM [73]. The Python *Apriori* algorithm requires an input of data and a declaration of minimum thresholds for the three measures of association: *Support, Confidence, and Lift*. Initially, these thresholds are set low to maximize the data returned to learn the relationships between *components-functions-flows* and *users tasks*. The minimum thresholds were set for this work to *Confidence* = 0.05, *Support* = 0.001, and *Lift* = 1. *Lift* values greater than 1 indicate the presence of an association rule; greater *Lift* values indicate stronger relationships between the *components-functions-flows* and *users tasks*.

The steps used during the design of an electric kettle to generate and validate the association rules using the *Apriori* algorithm are illustrated in Figure 3 and described next.

- **Step 1. Extract Similar Functional Models**. A subset of six coffeemakers is extracted from the Design Repository. For this study, a coffeemaker is selected because its operations require similar user interactions to the operation and control of an electric kettle.
- **Step 2. Algorithm generates Association Rules.** The *Apriori* algorithm is applied to the coffeemakers subset. The coffeemaker dataset has 35 unique components and 393 components-functions-flows and user tasks combinations; from those, 152 combinations are unique. The algorithm's output is a list of itemsets (user task, inflow-function-outflow, and component) with Confidence, Support, and Lift measurements.
- **Step 3. Designers generate a functional model for the electric kettle.** Designers create a functional model of an electric kettle using the Functional Basis. The resultant functional model for the electric kettle is presented in Figure 4.
- **Step 4. Designers applied FHEDM to the new design.** In this step, Designers manually apply the FHEDM to the functional model of an electric kettle. The identified associations between functions-flows and user tasks are presented in Table 1. Next, the resultant associations are evaluated by comparing the results of the Apriori algorithm for the coffeemaker dataset with the FHEDM results identified by human designers in the electric kettle design. By comparing these similar products, we can find meaningful relationships between components-functions-flows and user tasks associations through repetition.

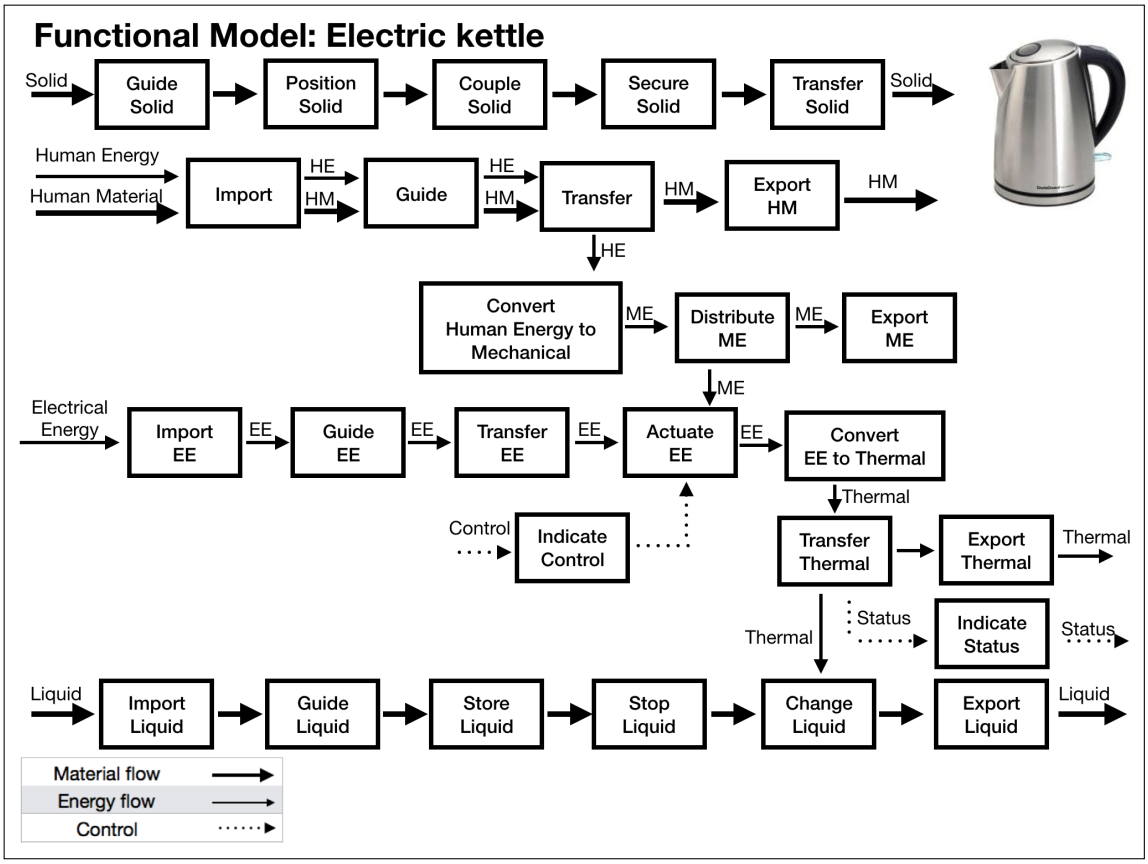

Fig. 4. Functional Model using the Functional Basis [15, 16] of an Electric kettle.

- **Step 5. Extract new design knowledge.** From the associations identified during the design of a new system, unexplored design information can be determined and used to extend the capabilities of the Design Repository. In this work, we are not adding new design knowledge to the Design Repository. Instead, we are examining the results to evaluate the capability of the Apriori algorithm to identify the associations. Future work will explore the application of resulting association rules to expand and refine the data in the Design Repository.

5 RESULTS

5.1 Apriori algorithm

The resulting associations from the Apriori algorithm for the coffeemaker subset are presented in Appendix A Tab. 4. The results allow us to identify specific associations between functions-flows, components, and user tasks and categorize such combinations. For example, the results extracted from the coffee maker dataset are presented using a Head and a Body.

Table 1. User tasks for Electric kettle - FHEDM

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
HE	import	HE	reaching
HE	guide	HE	grasping, carrying in the hands
HE	transfer	HE	pushing, pulling, turning, lifting
HE	convert	ME	pushing, pulling, turning, lifting
HM	import	HM	reaching
HM	guide	HM	grasping, carrying in the hands
HM	transfer	HM	pushing, pulling, turning, lifting
HM	export	HM	releasing
ME	distribute	ME	none
ME	export	ME	none
EE	import	EE	none
EE	guide	EE	none
EE	transfer	EE	none
EE	actuate	EE	manipulating, pushing, releasing
EE	convert	TE	none
TE	transfer	TE	none
TE	export	TE	none
CS	indicate	CS	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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS) Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE)			

- 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 present given a probability defined by what items are in the *flow-function-flow & component* combination.

The significance of the resulting associations can be assessed with Support (Eqn. 1), Confidence (Eqn.

2) and Lift (Eqn. 3) values. To describe what these values indicate, we took one result from Appendix A and presented it in Table 2.

Table 2. Extract from Appendix A: Apriori Algorithm Results Coffeemaker dataset

Body: user task	**Head: inflow-function-outflow & component**	**Confidence**	**Support**	**Lift**
grasping	HE-import-HE & electric switch	20.00%	0.80%	8.23

Support is the percentage of itemsets in the dataset that contains both the *user task* "grasping" and the *flow-function & component* set "Human Energy (HE)-import-HE & electric switch" together. For this example, only 0.80% of the coffeemakers data had these itemsets together.

Confidence is the percentage of itemsets in the dataset containing the *user task* "grasping", which also contains the *flow-function & component* set "HE-import-HE & electric switch". For this example, is the probability of having the *user task* "grasping", given that "HE-import-HE" (*flow-function-flow*), an electric switch (*component*) is already in the coffeemakers data. In other words, 20% of all those who select "HE-import-HE & electric switch", also include "grasping". From the functional models of coffeemakers present in the Design Repository, only 0.8% have the itemset: *Grasping* $\Rightarrow$ *HE-Import-HE & electric switch*.

However, given the *flow-function-flow-component* set "HE-import-HE-electric switch", it is somewhat likely (20%) that the *user task* "grasping" will be selected. This result confirms that if we have the functional model with the *flow-function-flow* "HE-import-HE" and the *component* "electric switch", there is a probability that 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 the user task (Eqn.3). *Lift* values greater than one indicates that the *flow-function-flow & component* is likely to be associated with the *user task*. Thus, the strength of the association is defined by larger *Lift* values. Conversely, *Lift* values lower than one indicates that the flow-function-flow-component are unlikely to be associated. Therefore, exists an association between: *Grasping* $\Rightarrow$ *HE-Import-HE & electric switch*.

From the results presented in Table 4, we selected meaningful associations with 100% Confidence, Support in the top half of all the recorded Support values, and Lift greater than "1". This threshold is selected to reduce falsely linking a *component* to a particular *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* are 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*.

The results presented in Appendix A: Table 4 reveal a snapshot of the information designers can extract from large data sets present in design repositories. Nevertheless, unique combinations between flows, functions, and components will require designers’ judgment to identify the accurate user tasks, as there is no appropriate amount of data to support data-mined associations confidently.

5.2 Associations for the Electric Kettle Model

This demonstration study evaluates the resulting association rules identified with the *Apriori* algorithm by comparing them to the associations identified by designers using the FHEDM. We compared the *functions, flows, and user interactions* identified by human designers using the FHEDM (Table 1) for the electric kettle with the associations derived from the algorithm for the subset of coffeemakers. Table 3 shows the comparison of the results. The left side of the table presents the associations built by the designers using FHEDM, while the right side presents the associations derived from the *Apriori* algorithm. The Lift value presents the strength of the resulting association rule generated by the algorithm. The results in the table are arranged into three categories *Identical Associations, Similar Associations, and Distinct Associations*.

The **Identical Associations** category groups the resulting itemsets *flow-function-flow and user tasks* that perfectly match the associations identified with FHEDM and those identified with the algorithm. From the results, only five association rules are identical in both groups. However, the Lift values are considerably low; only two association rules in this category have Lift values higher than 1.23.

The **Similar Associations** category groups the resulting itemsets that share similarities between the associations identified with FHEDM and those identified with the algorithm. From a product perspective, an electric kettle shares functional similarities with a coffeemaker, but they are distinct. Therefore, we do not expect to extract identical associations for all *functions, flows, and user tasks*. For our comparison, the functions and flows in a coffeemaker are slightly different and more complicated than those in an electric kettle. However, one can classify functions and flows that share similar functionality. For example, the electric kettle has the set *HE-transfer-HE*, which describes the user *grasping* the kettle. An equivalent function in the coffee maker dataset is the set *HE-convert-CS* which describes the user *pushing* the controls to operate the coffeemaker. The components in the Repository dataset support designers’ judgments to

Table 3. Comparison Association Rules - FHEDM & Apriori algorithm

Identical Associations					
Associations identified with FHEDM - Electric kettle		**Association Rules derived by *Apriori* algorithm - Coffeemaker**			
Inflow - Function - Outflow	**User task**	**User task**	**Component**	**Inflow - Function - Outflow**	**Lift**
HE - import - HE	reaching	reaching	housing	HE - import - HE	16.56
HM - guide - HM	grasping - carrying in the hands	carrying in the hand	handle	HM - guide - HM	12.42
EE - import - EE	none	none	electric cord	EE - import - EE	1.23
EE - convert - TE	none	none	heating element	EE - convert - TE	1.23
TE - transfer - TE	none	none	heating element	TE - transfer - TE	1.23
Similar Associations					
Associations identified with FHEDM - Electric kettle		**Association Rules derived by *Apriori* algorithm - Coffeemaker**			
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
HM - transfer - HM	pushing - pulling - turning - lifting	lifting	handle	HM - guide - HM	62.12
HE - transfer - HE	grasping - pushing - pulling - turning - lifting	pushing	electric switch	HE - convert - CS	41.42
CS - indicate - CS	watching - listening	manipulating	electric switch	CS - actuate - CS	27.62
HM - export - HM	releasing	manipulating	handle	HM - guide - HM	20.70
HE - guide - HE	grasping - carrying in the hands	grasping	system	HE - contain - HE	13.80
HM - import - HM	reaching	reaching	housing	HE - import - HE	16.56
ME - distribute - ME	none	none	electric cord	EE - supply - EE	1.23
ME - export - ME	none	none	electric switch	status - export - status	1.23
EE - guide - EE	none	none	electric wire	EE - supply - EE	1.23
EE - transfer - EE	none	none	mechanical transformer	EE - supply - EE	1.23
TE - export - TE	none	none	support	TE - transfer - TE	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 identified with FHEDM - Electric kettle		**Association Rules derived by *Apriori* algorithm - Coffeemaker**			
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
HE - convert - ME	pushing - pulling - turning - lifting	none	handle	HE - convert - translational	1.23
EE - actuate - EE	manipulating - pushing - releasing	none	electric switch	EE - actuate - EE	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

Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS) - Tactile Status (TS) - Visual Status (VS)
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE)

identify such similarities. For example, the electric kettle has the set *HM-export-HM and releasing*, similar to the set *HM-guide-HM and manipulating* with the component *handle*. This association describes the user *manipulating* the *handle* to guide the coffeemaker. The associations in this category are robust because the resulting Lift values are higher than 1.

The **Distinct Associations** category groups the resulting itemsets with no similarities between the as-

sociations identified with FHEDM and those identified with the algorithm. In this category, we find *function and flow* combinations that are identical or similar for both products. However, the *user task* item associated is different. These differences result from the similarity between *components and function-flows* for these products. For example, the set *solid-guide-solid* in the electric kettle is associated with the user task *grasping*, while for the coffeemaker, the set is associated with no user task and a *container* as a component. The solid material in the electric kettle functional model can be linked with a water container. Therefore, the user needs to grasp the container to transfer the water. On the contrary, the solid material in the coffeemaker can be associated with the ground coffee; depending on the type of coffeemaker, the user might not interact with ground coffee while the machine is operating. In these cases, the component's presence can help designers recognize and establish an association, but the algorithm fails to do so. The resulting associations' rules for this category have Lift values greater than 1.

6 DISCUSSION

In this work, we used a set of coffeemakers dataset from the Design Repository to determine association rules between *components, functions, flows, and user tasks* using an *Apriori* algorithm. The results are evaluated by comparing the associations generated by the algorithm to the associations created by designers using the Function Human Error Design Method (FHEDM). Designers with experience in functional models and actionfunction diagrams built the association rules for an electric kettle manually using the FHEDM. The electric kettle was selected for comparison because it shares similarities in form and function with a coffeemaker. By comparing these similar products, we can find meaningful relationships between components-functions-flows and user tasks associations through repetition.

The results reveal similarities between the associations generated with the algorithm and the FHEDM, supporting the proposed methodology and identifying meaningful correlations. The results confirm that designers can use association rules extracted from a design repository to identify user tasks from a functional model of a new design. The accuracy of the extracted associations rules depends on the quality and size of the original dataset. Nevertheless, even though the associations determined by the algorithm do not match 100% with the associations determined by designers using FHEDM, we observed meaningful similarities. Thus, confirming the capability of the proposed method to support designers in identifying and distinguishing relevant user-system interactions during early design stages. Although some resulting associations do not adequately connect flows and functions with user tasks, incorporating the relationship with a component allows designers to identify the missing user task.

The algorithm measurements metrics are set to Confidence 100%, Support in the top half of all the recorded supports, and Lift values over 1.27. These threshold values prevent the algorithm from falsely associating *function-flow-component* combinations with *user interactions*. For example, the results presented in in Appendix A: Table 4 include *function-flow-component* combinations associated with *no* user interaction. This result is expected because users will not interact with components such as gears, blades, screws, among others. Direct user interaction with such components can be a risk for the user's well-being. Additionally, the algorithm results can identify components associated with multiple human interactions based on function-flow combinations. Such associations are included in the results presented in Appendix A: Table 4. Future work will further analyze such associations to determine which user interactions and component associations are valid.

This research provides the basis for incorporating design knowledge into the Design Repository by first consolidating user-system interactions and failure modes associated with such interactions. Second, by building and refining the association rules between *functions, flows, components, and user tasks*. Third, by enhancing auxiliary design knowledge and decision support based on the physical user tasks required to perform and complete 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 inadequate user considerations, and failure modes caused by a component malfunction. Finally, this work demonstrates that this procedure is possible by extracting and generating design association rules from a rich and diverse set of data.

7 CONCLUSIONS

Identifying a set of possible user tasks from a functional model can enhance the design process by consolidating human factors principles during the early design stages. Additionally, it can bring to light design concepts that support user performance, comfort, and safety. Furthermore, it facilitates the analysis of failure modes caused by human-system interactions and components malfunction during the early design stages. Two shortcomings of manually building functional models and implementing FHDEM are the lexicon complexity and the inherent variability between human designers [12, 15, 22, 26, 47]. The functional basis [15, 16, 47, 74] and ICF lexicon [51, 52, 52–54, 68] used as a vocabulary for these methods are not intuitive for all designers making it hard to use, especially in industry. Additionally, designers can create multiple representations of functional models and actionfunction diagrams to describe the same system, and there is no right or wrong decision. The level of detail depends on the designer's perspective, experience, and

knowledge. This work contributes to the design community by developing the first steps towards automating the application of FHEDM during the design of new products and establishing association rules between *functions, flows, components, and user interactions* from a design repository.

In this work, the presented demonstration study uses a subset of products to establish association rules using an *Apriori* algorithm and identify possible anomalies in the data subset. This work validates the association rules extracted by an *Apriori* algorithm by comparing the results with the associations generated by designers with relevant expertise in functional models, Functional Basis, and action function diagrams. Consequently, designers with no experience in these design methods can use the associations extracted by the algorithms to identify and distinguish user interactions in a functional model during the design of a new product.

Furthermore, including the component with the function-flow-user tasks itemset allows the method to be applied with a more extensive set of consumer products within the Design Repository to scale up the generation of associations rules. However, the limited size and scope of the dataset used during this initial exploration restrict the designers' ability to distinguish user tasks from more extensive and more complicated functional models. Consequently, future work will explore different product families and expand the repository dataset by incorporating complex products and systems.

This work is part of the research accomplished by the Design Laboratory at Oregon State University (OSU) to develop an automated functional model generator tool. Such a tool will help designers standardize the language and syntax used in functional models, enabling the design of new products based on components, the functionality of the components, and 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 user's usability, performance, and safety while interacting with the product. Additionally, the resulting associations can be used to develop grammar rules to connect components to functions, flows, and user tasks. Finally, the presented work will be applied to a larger dataset that includes various 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 - COFFEEMAKER SUBSET

Table 4: Apriori algorithm results - Coffeemaker subset

Coffeemaker subset 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 CS	electric switch	25.00	0.20	41.41
pulling	HE convert CS	electric switch	25.00	0.20	41.41
pushing	HE convert CS	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	CS actuate CS	electric switch	16.67	0.20	27.61
pulling	CS actuate CS	electric switch	16.67	0.20	27.61
pushing	CS actuate CS	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
transferring oneself	HE import HE	visual indicator	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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
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	CS actuate CS	electric switch	16.67	0.20	7.53
grasping	CS actuate CS	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
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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
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	TE transfer TE	heating element	100.00	0.80	1.23
none	TE contain TE	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 TE	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	TE plate	100.00	0.60	1.23
none	solid couple solid	tube	100.00	0.60	1.23
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
none	solid position solid	TE plate	100.00	0.60	1.23
none	TE distribute TE	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
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	TE transfer TE	thermal plate	100.00	0.40	1.23
none	TE distribute TE	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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
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	TE transfer TE	cover	100.00	0.20	1.23
none	TE transfer TE	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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
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
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	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
Control Signal(CS) - Human Energy (HE) - Human Material (HM) - Status Signal (SS)					
Mechanical Energy (ME) - Electrical Energy (EE) - Thermal Energy (TE) - Tactile Status (TS) - Visual Status (VS)					
Continued on next page					

Table 4 – continued from previous page

Coffeemaker subset from Design Repository					
Body: User Task	**Head: inflow-function-outflow & component**		**Confidence**	**Support**	**Lift**
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

LIST OF FIGURES

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LIST OF TABLES

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