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Artificial Intelligence Assisted Social Failure Mode and Effect Analysis (FMEA) for Sustainable Product Design

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Abstract: Nowadays, the social dimension of product sustainability is increasingly in demand, however, industrial designers struggle to pursue it much more than the environmental or economic one due to their unfamiliarity in correlating design choices with social impacts. In addition, this gap is not filled even by the supporting methods that have been conceived to only support specific areas of application. To fill this gap, this study proposed a method to support social failure mode and effect analysis (SFMEA), though the automatic failure determination, based on the use of a chatbot (i.e., an artificial intelligence (AI)-based chat). The method consists of 84 specific questions to ask the chatbot, resulting from the combination of known failures and social failures, elements from design theories, and syntactic structures. The starting hypothesis to be verified is that a GPT Chat (i.e., a common AI-based chat), properly queried, can provide all the main elements for the automatic compilation of a SFMEA (i.e., to determine the social failures). To do this, the proposed questions were tested in three case studies to extract all the failures and elements that express predefined SFMEA scenarios: a coffee cup provoking gender discrimination, a COVID mask denying a human right, and a thermometer undermining the cultural heritage of a community. The obtained results confirmed the starting hypothesis by showing the strengths and weaknesses of the obtained answers in relation to the following factors: the number and type of inputs (i.e., the failures) provided in the questions; the lexicon used in the question, favoring the use of technical terms derived from design theories and social sustainability taxonomies; the type of the problem. Through this test, the proposed method proved its ability to support the social sustainable design of different products and in different ways. However, a dutiful recommendation instead concerns the tool (i.e., the chatbot) due to its filters that limit some answers in which the designer tries to voluntarily hypothesize failures to explore their social consequences.

Keywords: social FMEA; artificial intelligence; chatbot; social sustainability

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1. Introduction

In recent years, the social dimension of the sustainability of a product has acquired increasing importance, alongside the environmental and economic ones, in various sectors [1–3]. The creation of a more socially sustainable product passes from socially responsible design, according to which the designer ensures that the product does not negatively affect certain social values of the user and the population during its entire life cycle. Thus, the heart of socially responsible design is to avoid the potential harmful impacts of the product [4].

This task can be conducted according to the logic of the anticipatory failure investigation by referring the failures to social problems. In this regard, in the scientific literature, there are only a few recent contributions, which are mainly based on the social failure mode and effect analysis (SFMEA). The latter is an evolution of the traditional FMEA that allows one to frame and classify the possible social failures of a product, right from its conception, through the introduction of a dedicated ontology, in turn modified by that of the FMEA failures [5].

The cornerstones of FMEA, are on the one hand, the identification of the possible failures of the analyzed product or process, and on the other hand, the assessment of the risk of their occurrence, which is closely related to the ways in which the failures are expressed. In this regard, in the FMEA, a failure is described through three ontological elements [6]. Failure mode (FM) is the specific manner or way in which a failure occurs in terms of failure of the part, component, function, equipment, subsystem, or system under investigation. Failure effect (FE) is the immediate consequences of a failure on operation, or more generally on the needs for the customer/user that should be fulfilled by the function, but now is not, or not fully, fulfilled. Failure cause (FC) is a defect in the requirements, design, process, quality control, handling, or part application, which is the underlying cause or sequence of causes that initiate a process (mechanism) that leads to a failure mode over a certain time.

However, to also add the perspective of social sustainability, the determination of the failures in the SFMEA must take into consideration many more aspects than in the traditional FMEA, where social sustainability is almost always considered limited to the sole impact of health and safety [7]. Therefore, as has already been done in traditional FMEA [8], artificial intelligence (AI) could also support failure identification in the SFMEA, reducing the time and costs and increasing the quality and quantity of information that constitute the description of a failure.

This work proposes the use of a chatbot (i.e., AI-based chat), in support of the SFMEA, through an ad hoc developed method that consists of a series of 64 targeted questions to be asked in the same chat. The purpose of these questions is to identify the social failures associated with each part/component of a product and have been constructed by combining known failures of the same, in variable numbers, with a targeted lexicon and a specific syntactic structure. The method was then tested to derive the SFMEA relating to three scenarios of the social unsustainability of three products designed or used incorrectly, which were defined a priori: a coffee cup that causes gender discrimination, a COVD mask that denies a human right, a thermometer that undermines the cultural heritage of a community. The objective of the test is to evaluate the effectiveness of the method in relation to the type of output (i.e., the identified social failure), the input (i.e., how many and which social failures are necessary to know to obtain the desired result), and the application (i.e., the type of product and social impact).

The proposed method introduces some novelties compared to the previous contributions in the literature.

- The compilation of the SFMEA is supported by the AI. Previously, AI was only used to support FMEA, not SFMEA, and mostly for risk assessment related to failures, rather than to determine failures [9].
- The supported design activity is intrinsically aware of social sustainability. Previously, the implications of this aspect on the design have been little studied and without offering a practical and pragmatic framework to systematize the intersection [10].
- The reliability of a chatbot (i.e., Chat GPT) was tested for the first time in determining the social impacts arising from design bias. Before, chatbots were only used to support the generation of solutions in design without correlating them with other aspects [11].
- The intersection between SFMEA (and more in generally FMEA) and AI has been studied in a general way, unlike previous studies that worked in very specific application domains [12].

The rest of this study is organized as follows. Section 2 presents a brief introduction about the FMEA ontology and the literature background about SFMEA and the intersections between FMEA and AI. Section 3 presents the proposed method with the full list of the proposed questions. In Section 4, the results of the test of the proposed method are presented and discussed in relation to the efficacy of the same method. Finally, Section 5 presents our conclusions.

2. Literature Review

2.1. FMEA

The FMEA ontological elements form the basis of almost all FMEA evolutions (e.g., design FMEA, functional FMEA, and environmental FMEA). The main difference lies in the contextualization that is given to the ontological elements, which is then used to assess the risk associated with FE. For example, in traditional FMEA, the repercussions of failures refer to the health and safety of a generic user. In the environmental FMEA, they instead refer to present or future environmental impacts [13,14].

Some works have exploited AI to determine failures using different approaches (e.g., machine learning, neural network, Bayesian networks) [8,15]. Lately, some studies have begun to propose the use of chatbots to evaluate the environmental and economic repercussions of the failures [16]. Their undoubted advantage lies in the practicality of using the tool, given by the human–machine interaction through natural language, which makes it particularly suitable for non-experts as well as for teaching.

In this case, the limitations are different. Basically, only one type of failure (i.e., FM, FE, or FC) is determined and the links between different failures are not sought, for example, by looking for the link between the FMs and the individual components, or by defining only the FEs according to the scenario, or by re-investigating the FC looking for root causes [17]. The databases within which the failures are extracted have a limited number of sources and derive from on-site surveys on a limited number of products/plants and operational scenarios (e.g., machinery maintenance reports) [18]. The developed methods are almost always domain-specific or have been tested only in a single application [12]. Sometimes, while determining the failures with the AI, the studies do not frame them precisely, as prescribed by the FMEA, for example, precluding the comparability of the results or their classification or their use to support certifications [19].

2.2. SFMEA

In SFMEA, FEs refer to some categories of social sustainability impacts (e.g., gender discrimination, stratification, paid work) [20]. The main difficulty to face in this sense is that SFMEA failures, like the same social impact categories, cannot be defined in an absolute way but depend on the reference context, which in turn includes the stakeholder and the operating environment [21]. In addition, failures referring to social impacts have continuous rather than instantaneous occurrence times. This is because a product conceived, even involuntarily, to create a certain social discrimination with its structure, continues to create it throughout its operational life, unlike one that creates repercussions on the user's health and safety as a consequence of the determination of a specific FM [22].

Determining the social impacts of a product is therefore a multidisciplinary activity, which must involve engineers and designers in a synergistic way alongside anthropologists, sociologists, and psychologists. This undoubtedly complicates the design process in terms of time, cost, and interactions. For this reason, several studies have questioned the possibility of using AI for this purpose to support designers and engineers [23]. The main limitation of these works, however, mainly concerns their proactive nature. They are especially useful for supporting socially responsible design, but neglect to correlate the repercussions on social sustainability of any product failures including design biases and errors. Finally, to date, AI has not yet been used to identify the repercussions on the various impacts of social sustainability that failures in the design and functioning of a product can have [7].

3. Methods

The proposed method consists of a series of questions to be asked to an AI, through a chatbot, each of which has the objective to obtain a specific element of the SFMEA ontology, as an answer, relating to a specific product. Each question was constructed by combining:

- Known SFMEA ontological elements, in variable number, which the designer must know or can hypothesize.
- Semantic elements, designed to link the SFMEA ontological elements within the sentence (e.g., "why", "attribute", "cause", etc.).
- Syntactic structure of the question, where the elements of the FMEA ontology and the semantic elements act as the subject, verb, direct object, and other elements of the sentence.

In detail, the considered SFMEA ontological elements derive in part from the traditional FMEA and in part from the SFMEA, which are:

- Product (Pr): is the object of design;
- Part (Pa): is a component of a multi-component product or a part of a mono-component product;
- FM: as in the canonical definition of the traditional FMEA (see Section 2);
- Social FE (SFE): are the only FEs related to a social impact, referring to a certain stakeholder, as in [5];
- Social FE category (SFEC): is one of the classes that collect the social impact referred to by the SFE. The considered SFECs were taken from [20], and they are: population change, family, gender, education, paid work, stratification, health and safety, human rights, social networks and communication, conflict and crime, cultural heritage and identity;
- FC: describes how the product FM leads to the SFE on stakeholder [5].

Since the SFMEA ontological elements can be defined in many different ways and express different concepts, different semantic elements can be used to construct meaningful questions including the SFMEA ontological elements. For example, consider the verbs that express negative repercussions on different social impacts: "increase" stratification, "deny" human rights. For convenience, most of the considered semantic elements have been classified by associating them with some semantic elements arrays (e.g., "attribute", "cause") (see Table 1).

Table 1. Semantic element arrays used within the proposed questions.

Attribute	Attribute, Characteristic, Damage, Failure, Failure Mode, Feature, Parameter
Cause	Cause, decrease, deny, discriminate, generate, impact on, increase, provoke, undermine, violate
Part	Component, element, part, subassembly
Through	By means of, through
With	Affected by, having, with

The syntactic structure of the question was rigorously constructed by considering different aspects to improve their effectiveness in research through the combination of SFMEA ontological elements and semantic elements. In particular, a form and an ontology typically used in problem solving for the identification of problems and their causes (i.e., those typically used to fill the Ishikawa diagram) were considered to formulate the questions, as suggested by [24]. In this way, the AI is directly interrogated with questions such as why, when, which part, etc.

Table 2 shows an example of a question, aimed at identifying the Pa of the product through two known SFMEA ontological elements (i.e., FM and SFEC) and using two semantic element arrays (i.e., "part" and "cause") within a certain syntactic structure of the question.

Table 2. Structure of a proposed question (where Pr = product, Pa = part, FM = failure mode, SFE = social failure affect, SFEC = social failure effect category, FC = failure cause).

Input					Question
Pa	FM	SFE	SFEC	FC	
	✓		✓		The [FM] of which part of the [Pr] cause [SFEC]?

3.1. Proposed Questions List

The proposed questions (see Table 2) were classified on two levels according to the searched SFMEA ontological element and the known ones that are provided in the questions to search it. The searched SFMEA ontological elements were Pa, FM, SFE, and FC, while all the combinations of known SFMEA ontological elements were explored in the construction of the questions except for the searched one, which is not known. In the following Tables 3–6, all the questions are reported.

Table 3 shows the questions proposed to identify Pa, specifying the known SFMEA ontological elements used as input by each of them.

Table 3. Questions used to identify the Pa.

Input					Question	
Pa	FM	SFE	SFEC	FC		
					Pa_1	Which part of the [Pr] cause social impact?
	✓				Pa_2	The [FM] of which part of the [Pr] cause social impact?
		✓			Pa_3	Which part of the [Pr] cause [SFE]?
			✓		Pa_4	Which part of the [Pr] cause [SFEC]?
				✓	Pa_5	Which part of the [Pr] the [FC] is associated with?
	✓	✓			Pa_6	The [FM] of which part of the [Pr] cause [SFE]?
	✓		✓		Pa_7	The [FM] of which part of the [Pr] cause [SFEC]?
	✓			✓	Pa_8	Which part of the [Pr] with [FM] the [FC] be associated with?
		✓	✓		Pa_9	Which part of the [Pr] cause [SFEC] through [SFE]?
		✓		✓	Pa_10	Which part of the [Pr] cause [SFE] cause [FC]?
			✓	✓	Pa_11	Which part of the [Pr] cause [SFEC] cause [FC]?
	✓	✓	✓		Pa_12	The [FM] of which part of the [Pr] cause [SFEC] through [SFE]?
	✓	✓		✓	Pa_13	Which part of the [Pr] with [FM] and [SFE] the [FC] is associated with?
	✓		✓	✓	Pa_14	Which part of the [Pr] with [FM] and [SFEC] the [FC] is associated with?
		✓	✓	✓	Pa_15	Which part of the [Pr] cause [SFEC] through [SFE] cause [FC]?
	✓	✓	✓	✓	Pa_16	The [FM] of which part of the [Pr] cause [SFEC] through [SFE]?

Table 4 shows the questions proposed to identify FM.

Table 4. Questions used to identify the FM.

Input					Question	
Pa	FM	SFE	SFEC	FC		
					FM_1	What attribute of the [Pr] cause social impact?
✓					FM_2	What attribute of the [Pa] of the [Pr] cause social impact?
		✓			FM_3	What attribute of the [Pr] cause [SFE]?
			✓		FM_4	What attribute of the [Pr] cause [SFEC]?
				✓	FM_5	What attribute of the [Pr] the [FC] can be associated with?
✓		✓			FM_6	What attribute of the [Pa] of the [Pr] cause [SFE]?
✓			✓		FM_7	What attribute of the [Pa] of the [Pr] causes [SFEC]?
✓				✓	FM_8	What attribute of the [Pa] of the [Pr] the [FC] can be associated with?
		✓	✓		FM_9	What attribute of the [Pr] cause [SFEC] through [SFE]?
		✓		✓	FM_10	What attribute of the [Pr] cause [SFE] is caused by [FC]?
			✓	✓	FM_11	What attribute of the [Pr] cause [SFEC] is caused by [FC]?
✓		✓	✓		FM_12	What attribute of the [Pa] of the [Pr] cause [SFEC] through [SFE]?
✓		✓		✓	FM_13	What attribute of the [Pa] of the [Pr] cause [SFE] is caused by [FC]?
✓			✓	✓	FM_14	What attribute of the [Pa] of the [Pr] cause [SFEC] is caused by [FC]?
		✓	✓	✓	FM_15	What attribute of the [Pr] cause [SFEC] through [SFE] is caused by [FC]?
✓		✓	✓	✓	FM_16	What attribute of the [Pa] of the [Pr] cause [SFEC] through [SFE] is caused by [FC]?

Table 5 shows the questions proposed to identify SFE.

Table 5. Questions used to identify the SFE.

Input					Question	
Pa	FM	SFE	SFEC	FC		
					SFE_1	What social impact can the [Pr] cause?
✓					SFE_2	What social impact can the [Pr] with [Pa] cause?
	✓				SFE_3	What social impact can the [Pr] with [FM] cause?
			✓		SFE_4	What [SFEC] can the [Pr] cause?
				✓	SFE_5	What social impact of a [Pr] is caused by [FC]?
✓	✓				SFE_6	What social impact can be caused by [Pa] with [FM] of the [Pr]?
✓			✓		SFE_7	What [SFEC] can the [Pr] with the [Pa] cause?
✓				✓	SFE_8	What social impact is caused by [FC] through [Pr] with [Pa]?
	✓		✓		SFE_9	Which [SFEC] can be affected by [Pr] with [FM]?
	✓			✓	SFE_10	What social impact is caused by [FC] through [Pr] with [FM]?
			✓	✓	SFE_11	Which [SFEC] can be caused by [FC] through [Pr]?
✓	✓		✓		SFE_12	Which [SFEC] can be caused by [Pa] with [FM] of the [Pr]?
✓	✓			✓	SFE_13	What social impact can be caused by [FC] through the [Pa] with [FM] of the [Pr]?
✓			✓	✓	SFE_14	Which [SFEC] can be caused by [FC] through [Pa] of the [Pr]?
	✓		✓	✓	SFE_15	Which [SFEC] can be caused by [FC] through [Pa] with [FM]?
✓	✓		✓	✓	SFE_16	Which [SFEC] can be caused by [FC] through [Pa] with [FM] of the [Pr]?

Table 6 shows the questions proposed to identify FC.

Table 6. Questions used to identify the FC.

Input					Question	
Pa	**FM**	**SFE**	**SFEC**	**FC**		
					FC_1	Why [Pr] cause social impact?
✓					FC_2	Why the [Pa] of the [Pr] cause social impact?
	✓				FC_3	Why the [Pr] with a [FM] cause social impact?
		✓			FC_4	Why [Pr] cause [SFE]?
			✓		FC_5	Why [Pr] cause [SFEC]?
✓	✓				FC_6	Why the [Pa] with [FM] of the [Pr] cause social impact?
✓		✓			FC_7	Why the [Pa] of the [Pr] cause [SFE]?
✓			✓		FC_8	Why the [Pa] of the [Pr] cause [SFEC]?
	✓	✓			FC_9	Why the [Pr] with [FM] cause [SFE]?
	✓		✓		FC_10	Why the [Pr] with [FM] cause [SFEC]?
		✓	✓		FC_11	Why the [Pr] cause [SFEC] through [SFE]?
✓	✓	✓			FC_12	Why the [Pa] with [FM] of the [Pr] cause [SFE]?
✓	✓		✓		FC_13	Why the [Pa] with [FM] of the [Pr] cause [SFEC]?
✓		✓	✓		FC_14	Why the [Pa] of the [Pr] cause [SFEC] through [SFE]?
	✓	✓	✓		FC_15	Why the [Pr] with [FM] cause [SFEC] through [SFE]?
✓	✓	✓	✓		FC_16	Why the [Pa] with [FM] of the [Pr] cause [SFEC] through [SFE]?

The proposed questions were tested in three case studies involving three different products that can have different social impacts if subjected to design bias or damaged during their lifetime. The objective of this test was to verify whether and which of the proposed questions are more suitable for identifying the SFMEA ontological elements of each product for reconstructing the SFMEA in a specific negative scenario for social sustainability, where this scenario can be described with a SFMEA ontological element of any type.

3.2. Case Studies

In the following, the descriptions of the three different products and of the negative scenarios (i.e., a coffee cup provoking gender discrimination, a COVID mask denying a human right, and a thermometer affecting the cultural heritage of a community) are presented in detail with reference to the SFMEA ontological elements.

A coffee cup is not intended to create gender discrimination. However, its handle can be perceived to better accommodate the men if the size is too big [25]. This case study draws inspiration from this fact to construct a SFMEA scenario, where a coffee cup (i.e., Pr) has a handle (i.e., Pa) that has been erroneously designed with a size that is too small or too large in relation to its internal circumference and/or the diameter (i.e., FM). The consequence on the social sustainability of this FM is the discrimination of users with big hands, if the size of the handle is too small, or small hands, if the size of the handle is too big (i.e., SFE), respectively. Such SFE can be related, in most cases, to gender discrimination (i.e., SFEC). While the cause of this SFE is due to the difficulty to grab and hold the coffee cup by men or women with different sizes of hands and fingers (i.e., FC) [26].

The use of a surgical mask was a clearly effective preventive measure to counter the COVID infection and its spread, thus having a positive repercussion on social sustainability in relation to the health and safety impact. However, the same mask, in its most widespread models, has also represented an impediment to communication, especially for deaf people [27]. The SMFEA scenario of this case study correlates the opacity (i.e., FM) of the material of the front part covering the mouth (i.e., Pa) of a COVID mask (i.e., Pr) to the discrimination of deaf people in communication (i.e., SFE). This social impact can be classified as the denial of a human right (i.e., SFEC) and is due to the avoidance of lip reading (i.e., FC), which is necessary for deaf people to communicate.

The reduction and abandonment of traditional fishing by various Aboriginal communities of Canada living along the watercourses, starting from the seventies, has been correlated to mercury pollution also deriving from the incorrect disposal of thermometers [28]. In this case, the SFMEA scenario that was considered concerned the leakage due to structural damage during the operational life or disposal (FM) of the mercury (Pa) from a thermometer (Pr). The consequence on social sustainability deriving from this, which was considered in this case study, is the impact on the fishing habits of a community (SFE), which can be classified in the social impact category of cultural heritage (SFEC), while the cause of SFE has been associated with fish contamination (FC).

Figure 1 provides representations of the three considered case studies.

Figure 1. The considered case studies of socially unsustainable products. A coffee cup causing gender discrimination in women with small fingers or men with big fingers. A COVID mask denying human rights by avoiding the lip reading of deaf people. A thermometer undermining cultural heritage by poisoning the fish through mercury leakage.

Table 7 summarizes the SFMEA scenarios in the considered case studies.

Table 7. The SFMEA scenarios in the considered case studies.

Pr	Pa	FM	SFE	SFEC	FC
Coffee cup	Handle	Wrong size (too small/too big)	Discriminate users with big hands/small hands	Gender discrimination	Difficulty to grab and hold the coffee cup
COVID mask	Part in front of the mouth	Opacity	Discriminate death people to communicate	Human right	Avoiding lip reading
Thermometer	Mercury	Leakage	Fishing habit of a community	Cultural heritage	Fish contamination

3.3. Test Execution

The test was performed by submitting all the proposed questions for each case study to a chatbot (i.e., ChatGPT) and evaluating the obtained answers. Each question was constructed by inserting known SFMEA ontological terms of the relevant case study (see Table 7) together with the semantic elements within its syntactic structure. While each response provided by the chatbot was evaluated by the authors themselves in two ways (i.e., yes/no), depending on the explicit presence of the searched SFMEA ontological term of the relevant case study.

This is because, as the proposed method was developed, it can be applied by a designer who asks the AI questions, or by a non-sentient computer that does not have to interpret the answer to report a correlation between the ontological SFMEA elements, for example, in an automatically constructed table. For this reason, in the test, the answer given by the AI "Communication: The opacity of the mask can make it difficult for individuals to communicate verbally, which can affect their ability to express themselves freely, and can make it difficult for deaf and hard- of-hearing individuals to read lips and communicate effectively" was not positively evaluated for providing the Pa (i.e., the part of the mask that covers the mouth). This is because a human can easily understand that the part of the mask that prevents lip reading is the one in front of the mouth, but a computer cannot.

4. Results and Discussion

4.1. Test Results

Table 8 shows the outcomes of the test for each question and for each case study as well as reports the score of the question, given by the sum of the positive results in the three case studies.

Table 8. Results of the test for each question in the case studies.

Output	Input					Question	Case Studies			
	Pa	FM	SFE	SFEC	FC		Coffee Cup	COVID Mask	Thermometer	Score
Pa						Pa_1	No	No	No	0
		✓				Pa_2	No	Yes	Yes	2
			✓			Pa_3	Yes	Yes	No	2
				✓		Pa_4	No	No	No	0
					✓	Pa_5	Yes	Yes	No	2
		✓	✓			Pa_6	Yes	Yes	Yes	3
		✓		✓		Pa_7	Yes	No	No	1
		✓			✓	Pa_8	Yes	Yes	No	2
			✓	✓		Pa_9	Yes	No	No	1
			✓		✓	Pa_10	Yes	Yes	No	2
				✓	✓	Pa_11	Yes	No	No	1
		✓	✓	✓		Pa_12	Yes	Yes	Yes	3
		✓	✓		✓	Pa_13	Yes	Yes	Yes	3
		✓		✓	✓	Pa_14	Yes	Yes	Yes	3
			✓	✓	✓	Pa_15	Yes	Yes	No	2
		✓	✓	✓	✓	Pa_16	Yes	Yes	No	2
FM						FM_1	No	No	No	0
	✓					FM_2	Yes	No	Yes	2
			✓			FM_3	Yes	No	No	1
				✓		FM_4	No	No	No	0
					✓	FM_5	No	Yes	No	1
	✓		✓			FM_6	Yes	Yes	Yes	3
	✓			✓		FM_7	Yes	Yes	No	2
	✓				✓	FM_8	Yes	Yes	Yes	3
			✓	✓		FM_9	Yes	No	No	1
			✓		✓	FM_10	Yes	Yes	No	2
				✓	✓	FM_11	Yes	Yes	No	2
	✓		✓	✓		FM_12	Yes	Yes	Yes	3
	✓		✓		✓	FM_13	Yes	No	Yes	2
	✓			✓	✓	FM_14	No	Yes	Yes	2
			✓	✓	✓	FM_15	Yes	Yes	No	2
	✓		✓	✓	✓	FM_16	Yes	Yes	Yes	3
SFE						SFE_1	No	No	No	0

	✓					SFE_2	No	No	No	0
		✓				SFE_3	No	Yes	No	1
				✓		SFE_4	Yes	No	No	1
					✓	SFE_5	No	No	No	0
	✓	✓				SFE_6	Yes	No	No	1
	✓			✓		SFE_7	No	Yes	Yes	2
	✓				✓	SFE_8	Yes	Yes	Yes	3
		✓		✓		SFE_9	Yes	Yes	No	2
		✓			✓	SFE_10	No	No	No	0
				✓	✓	SFE_11	No	Yes	Yes	
	✓	✓		✓		SFE_12	Yes	Yes	Yes	3
	✓	✓			✓	SFE_13	No	Yes	No	1
	✓			✓	✓	SFE_14	No	Yes	Yes	2
		✓		✓	✓	SFE_15	Yes	Yes	Yes	
	✓	✓		✓	✓	SFE_16	Yes	Yes	Yes	3
FC						FC_1	No	No	No	0
	✓					FC_2	No	Yes	Yes	2
		✓				FC_3	No	Yes	Yes	2
			✓			FC_4	Yes	Yes	No	2
				✓		FC_5	No	No	No	0
	✓	✓				FC_6	Yes	Yes	Yes	3
	✓		✓			FC_7	Yes	Yes	Yes	3
	✓			✓		FC_8	Yes	No	Yes	2
		✓	✓			FC_9	Yes	Yes	Yes	3
		✓		✓		FC_10	No	No	No	0
			✓	✓		FC_11	Yes	Yes	No	2
	✓	✓	✓			FC_12	Yes	Yes	Yes	3
	✓	✓		✓		FC_13	Yes	Yes	No	2
	✓		✓	✓		FC_14	Yes	Yes	Yes	3
		✓	✓	✓		FC_15	Yes	Yes	Yes	3
	✓	✓	✓	✓		FC_16	Yes	Yes	Yes	3

From the analysis of the results obtained in the three considered case studies, the proposed method proved to be sufficiently capable of identifying the SFMEA ontological elements: of all the 192 questions in the three case studies, 60% led to a positive outcome. In more detail, in relation to the obtained output, the questions looking for HR proved to be the most effective with 69% of positive results, followed by those looking for Pa and FM, both with 60% of positive results and finally from those of the SFE, where the positive outcomes were equal to 50%.

The number of inputs used clearly influences the outcome of the answers, according to a direct proportionality. In fact, the questions that gave a positive result were 0% with 0 inputs, 38% with one input, 64% with two inputs, 83% with three inputs, and 92% with four inputs. Analyzing the type of used input, it emerged that the questions including the SFE obtained the highest number of positive outcomes (i.e., 79%), followed by those with the Pa (78%), FM (72%), FC (67%), and finally, SFEC (with 64%).

4.2. Discussion of the Results

Going into the merits of the results, some considerations emerged that were duly investigated. On one hand, the influence of semantic choices relating to the terms was noted (i.e., deriving from ontologies or not) used in questions about the goodness of the provided answers. On the other hand, the limitations of the method, deriving from the use of the tool (i.e., the chatbot) emerged. In the following, these considerations are presented in detail.

4.2.1. Semantical Choices

In general, the questions including a technical term, deriving from an ontology, obtained a greater number of answers containing the searched SFMEA ontological elements compared to those constructed with generic terms. This was found to be true for two categories of ontological terms derived from the following taxonomies of:

- Design theories (e.g., function–behavior–structure (FBS) theory) [29] to detail the question in the part where the unknown SFMEA ontological element is sought (e.g., the FM);
- Social sustainability (e.g., European Union (EU) Social Taxonomy [30], to detail the part of the question that specifies the repercussions of the failures on social sustainability (i.e., to more precisely express the known SFE and SFEC).

For example, answers that provided the SFME ontological element sought to question those including a design ontology technical term (e.g., "attributes"), which were 69%, or 9% more than the average. In more detail, Table 9 presents a comparison between two questions referring to the FM_7 model (expected output: FM, input: Pa, SFEC), contextualized in the case study of the COVID mask. From the first question, which used the combination of ontological design terms "design attribute of the structure", the chatbot returned the FM (i.e., "opacity") in the answer, while in the second one it did not.

Table 9. Examples of questions containing/not containing terms from the design ontologies.

Used Ontological Terms	Question	Result
With terms from the design ontologies	What design attribute of the structure of the part of a COVID mask that covers the mouth affects human rights?	Yes
Without terms from the design ontologies	How/why/when/in which case/what characteristic of the part of a COVID mask that covers the mouth affect human rights?	No

While an example of the effectiveness of the use of the terms of the social sustainability taxonomies concerned question FC_13 (expected output: FC, input: Pa, FM, SFEC), in which ontological terms derived from the EU Social Taxonomy were used to express the SFEC and generic terms. In the first case, the question made it possible to obtain the sought FC (i.e., "fish contamination") unlike the question in which the SFEC was expressed in a generic way (i.e., "cultural heritage") (see Table 10).

Table 10. Examples of questions containing/not containing terms from the ontologies of social sustainability.

Used Ontological Terms	Question	Result
Terms from the ontologies of social sustainability	Why the leakage of the mercury in a thermometer undermines class "Heritage Preservation activities" of the group "91.05—Conservation-Restoration activities" of the Statistical Classification of Economic Activities?	Yes
Without terms from the ontologies of social sustainability	Why the leakage of the mercury in a thermometer undermines cultural heritage?	No

Therefore, this evidence would therefore confirm the hypothesis that a user who communicates with an AI chatbot using technical terms has a better chance to obtain relevant and precise information, which are also already wrapped up in other applications ([31,32]) in the context of FMEA compilation and AI-assisted product design. Therefore, in this specific case of application, the user must pay attention to the choice of semantic elements in the construction of the questions, for example, by favoring those of the FMEA and the design ontology (see Table 1).

4.2.2. Limitations of the Tool (i.e., Chatbot)

The test also revealed that the case studies, and consequently the different types of investigated social impact, have an influence on the outcome of the questions. Those referring to the cases of the coffee cup and the COVID mask both obtained 67% of positive results, while those referring to the thermometer obtained only 45% of the positive results.

In more detail, in the first case study, certain responses from the AI provided the correlation between the size of the user's hands and gender (i.e., the SFE and the SFEC), while other times they did not, while providing the sought SFMEA ontological element (e.g., FC). For example, to question FC_8 (expected output: FC, input: Pa, SFEC), the AI provided the answer with the correlation between SFE (i.e., "the small size of the handle") and SFEC (i.e., "women") while to question FC_15 (expected output: FC, input: PM, SFE, SFEC), the AI did not provide this correlation in its answer (see Table 11).

Table 11. Examples of answers provided by the AI affected not influenced (to question FC_8) and influenced (to question FC_15) by the polite filter of the chatbot, when the objective is to correlate the size of the hands and gender.

Question	Answer
Why the handle of a coffee cup causes gender discrimination? (FC_8)	If the design or positioning of the handle is such that it is difficult for certain groups of people such as women or those with smaller hands to hold or use the cup comfortably, it could be considered as a form of discrimination
Why a coffee cup with a too small part causes gender discrimination in users with small or big hands? (FC_15)	A coffee cup with a too small handle may cause difficulty for some users with larger hands to comfortably hold, as the handle may not be able to accommodate their fingers. In this way, a coffee cup with a poorly designed handle may create an inconvenience for certain users, but it does not inherently discriminate based on gender

This fact represents a problem, especially if the objective is to automate the proposed method, since the lack of correlation between FM or FC with SFEC does not allow a non-sentient computer to provide suggestions to support socially responsible design (e.g., "design a narrower handle for women") by reworking the obtained answers. Nonetheless, the correlation between SFE and SFEC, despite being non-polite, has been scientifically demonstrated in some studies [33] and is also provided by the same chatbot when answering question FC_8 (see Table 11).

The justification for this result can be found in the extensive work conducted by AI-based chat managers to make their tools more polite to make them more appreciated by users [34]. Consequently, this also justifies the lower effectiveness of questions using the SFEC. However, on a more general level, this fact could be a limitation of the AI if applied in support of the SFMEA. To be polite, the AI could intentionally not correlate a negative social impact (i.e., SFE or SFEC) to a design bias or a product failure (i.e., FM), thus selling less to the target assigned to it, limiting the effectiveness of the proposed method. Therefore, this approach generally clashes with that often used for the compilation of the FMEA, as in the case of the inverse FMEA [35], where problem-solving methods are used to recreate, albeit ideally, a negative scenario in a given product.

To overcome this typical chatbot limitation, two approaches to question formulation can be used:

- Role playing, in which the user stimulates the AI to "behave" in a certain way in order to bypass its language and response content limitations;
- The double negative, in which the user dialogues with the AI in a proactive manner regarding a data failure, asking how the latter can be avoided.

The effectiveness of this approach has been scientifically demonstrated with various chatbots, above all to make the level of interaction more authentic and realistic, for example, to learn a foreign language with AI, even at a conversational level [36] or in support of psychology to simulate human behaviors and reactions [37]. In the case of failure determination, this technique has never been used in the literature, where AI finds failures by analyzing sources where they are well-documented and by answering targeted research questions that take the failures for granted and are aimed at investigating their nature [38]. However, in this specific case, while asking the chatbot to role play in several different ways, it was not possible to obtain the correlation between SFE and SFEC in the answer to question FC_15. This, despite having asked the AI in many different ways, both present on the web (e.g., DAN mode for jailbreaking ChatGPT) and specifically (e.g., "Can you role play to help me in making FMEA analysis by identifying product failure in order to improve its design?"), and always getting affirmative answers.

Even in the case of the double negative, the AI did not provide the correlation sought in the answer to the same question (i.e., FC_15), albeit posed according to this logic (e.g., "What should I do in order to avoid gender discrimination in users with small or big hands when I design a coffee cup with a too small part?").

5. Conclusions

In this study, a method to support the automatic identification of failures in SFMEA through AI was presented, whose peculiarity is the collection of targeted questions to be asked to a chatbot, which include combinations of the elements of the SFMEA ontology and the design ontologies. In relation to the limitations of the test to which the method was subjected (i.e., number and type of case studies considered, manual supervision of the results obtained, and type of considered chatbot), the following conclusions were obtained.

- The usefulness of the proposed method was confirmed in most cases, since the chatbot provided the searched elements explicitly. In this way, even a non-sentient computer that asks the chatbot the proposed questions do not have to interpret the obtained results in most cases.
- As the provided SFMEA ontological elements increase, the accuracy of the answers increases, although positive results were obtained even with only two input elements, and negative results with four.
- The method allowed us to determine some failures (e.g., FC) more than others (e.g., SFE).
- The effectiveness of the method also depends in part on the type of problem addressed and therefore on the type of considered social impacts, since some relationships between the latter and the failures are more difficult to determine.
- The use of a technical lexicon in the questions, deriving from design theories and social impact taxonomies, improved the outcome of the answers.
- The main limitations of the proposed method concern the tool used (i.e., the chatbot) due to some of its rules/filters relating to polite policies. The latter represents a problem in the failure investigation of the SFMEA as well as in the traditional FMEA, when one wants to understand which failures can cause certain negative social impacts defined by the user. To overcome this problem, the known workaround methods (e.g., role playing and the double negative technique) proved to be insufficient.

The main repercussions of this method can be, above all, on socially responsible design to understand which design bias to avoid in order to improve or not to compromise the social sustainability of the product. In this context, the proposed method, albeit with questions of simple construction and which presuppose little knowledge of the product and of the FMEA/SFMEA, has made it possible to fill in the knowledge gap on the social sustainability of the product that typically any engineer does not possess.

Future developments of this method may concern the expansion of case studies, and also the testing of its effectiveness in correlating other types of social impacts to failures and design biases. At the same time, the method can be refined in the formulation of the questions, deepening the role of the choice of the ontological elements to be used. Finally, it is also possible to improve the user's interaction with the AI by studying and experimenting with solutions that make it possible to circumvent the existing limits that partially compromise the effectiveness of the proposed method.

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Nomenclature

FMEA	Failure Mode and Effect Analysis
SFMEA	Social Failure Mode and Effect Analysis
AI	Artificial intelligence
Pr	Product
Pa	Part
FM	Failure mode
FE	Failure effect
SFE	Social FE
SFEC	Social FE category
FC	Failure cause

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