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Manual and Automatic Methods for User Needs Detection in Requirements Engineering: Key Concepts and Challenges

Joni Salminen
Qatar Computing Research Institute, Hamad Bin Khalifa University; and Turku School of Economics at the University of Turku
Doha, Qatar
jsalminen@hbku.edu.qa

Soon-Gyo Jung
Qatar Computing Research Institute, Hamad Bin Khalifa University
Doha, Qatar
sjung@hbku.edu.qa

Bernard J. Jansen
Qatar Computing Research Institute, Hamad Bin Khalifa University
Doha, Qatar
bjansen@hbku.edu.qa

***Abstract*— User needs inform designers and developers of essential functionalities for requirements engineering. In this work, we summarize key concepts and challenges relating to manual and automatic user needs detection methods. We discuss six challenges with manual and eight challenges with automated methods. Despite the promise of automated methods, the challenges imply that artificial intelligence and machine learning are not yet mature enough to replace manual methods, such as interviews and focus groups, for discovering user needs in requirements engineering.**

Keywords*— *user needs, user needs detection, requirements engineering, user research

I. Introduction

Successful engineering of products and services depends on a deep understanding of *user needs*. Without information on user needs, new products and services are likely to fail in the marketplace [1]. User needs are defined as explicit expressions of a user's goals, values, and aspirations from a user regarding a real or potential service or product [2]. User needs are first identified via *user needs detection* and then transformed into features or functionalities to accommodate users' expectations from a product or service to accomplish their goals. This is done via *requirements engineering*, which is defined as the process of determining, detailing, and updating development items (i.e., requirements) for systems or software engineering.

Early stage of the design process is central to product development, since it is the period when user needs are elicited and transformed into concrete product specifications [3]. If user needs are not interpreted correctly, design defects and redundant features may ensue. As such, understanding user needs is crucial for feeding "raw material" into the engineering design process. By *users*, we mean end-users of products (i.e., those for whom the product or service is intended) – similar conceptualizations include customers (those who buy the product), consumers, or buyers (especially when using the lens of marketing [4]).

To detect user needs, requirements engineering and associated fields such as human-computer interaction (HCI) and marketing have applied a range of methods. These include manual means, such as focus groups, interviews and surveys, as well as newer, automated machine learning (ML) based approaches, which are capable of handling the "big data" [5] that organizations encounter daily [5], [6]. These ML techniques can identify language patterns in digital data [7], and provide critical insights into user values and preferences in large user research datasets. This scalability and broad applicability of automation has understandable resulted in heightened interest in the use of unsupervised learning and natural language processing (NLP) for requirements engineering.

While both manual and automatic methods have significant strengths in their own right, they also possess weaknesses that can affect the feasibility and quality of the outcomes; and thus, their usefulness to user needs detection for requirements engineering. Awareness of these challenges can help developers (a) to pick appropriate methods for their engineering use case and, as a result, (b) to produce more relevant knowledge of user needs, thereby improving the user-centricity of the developed engineering solution.

Additionally, the methods for user need detection for requirements engineering are varied to the degree that their understanding can be complex and confusing, especially for those new to user research. This is why summarizing user need detection methods for the engineering research community comprises a useful contribution. Critically reviewing different methods for user needs detection helps (a) direct future research to address the challenges of understanding users in requirements engineering, and (b) inform practitioners engaged in user research about the current challenges in the field. Given the rise of artificial intelligence (AI) and ML techniques for user research and society at large, acquiring knowledge of the limitations of these techniques for requirements engineering helps requirements engineers do better in their jobs.

This research presents an overview exploring methods in user needs detection. Our analytical goal is to compare "traditional" manual methods and "novel" automated methods for user need detection, summarize how these methods have been applied, and what are their key challenges for user need discovery for requirements engineering in product and service development.

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II. Central concepts

This section provides definitions for terms that appear repeatedly in user needs detection literature. Hence, these concepts help the reader understand the key concepts used in the literature. Definitions for most manual and automated methods are not included since this information is provided in later sections.

Different terms for user needs. Terms used to refer to user needs varies across academic disciplines, with words such as “needs,” “wants,” “requirements,” “characteristics” and “attributes” often used interchangeably in the literature, even though they have independent meanings [8], [9]. In general, user (or customer) needs can be described as what a user (or customer) desires from a product or service [10], [11]. Alternatively, attributes, features, characteristics, and requirements are words that describe how a need is satisfied. For example, the term requirements is used in engineering to refer to technical solutions that fulfil user needs [8]. In HCI and marketing, user attributes are the objective properties of a product or system that are meaningful for users [8], [12]–[15], and are sometimes organized in user need taxonomies [16]. Observable or explicit needs are clearly stated in speech or text (e.g., “I want faster horses”), while latent needs are desires or preferences that users do not realize they possess [17]. Although text and speech can be used towards detecting latent user needs, some needs cannot be conveyed through language but are only evident in people’s behaviors or physical responses [18], [19]. Hence, detecting latent needs involves more “guess work” and methodological sophistication.

Varied concepts for user needs detection. Similar to variability of “user needs” in literature, the detection thereof is conceptually varied. Terms used, often interchangeably, include user needs detection, voice of the customer (VOC), user need discovery, requirements engineering, inference of latent needs, customer understanding, and needfinding, among others [18, 52, 8]. The shared definition of these concepts is that they refer to a set of methods that focus on eliciting user needs, both explicit and latent (i.e., indirectly expressed needs) to inform product design [22]. For simplicity, we use the concept of ‘user needs detection’ to refer to these activities. User needs detection helps product designers to understand the wants, preferences, and expectations of users by focusing on user needs, hierarchy, priorities, and segmentation. To identify needs, researchers use qualitative or quantitative methods to reveal user perspectives and experiences. Next, researchers create a hierarchy of primary, secondary, and tertiary needs based on user statements. These needs are then assigned a priority reflecting their value to users. Segmentation refers to the variability in user needs. If user needs differ among groups due to needs, hierarchies and priorities, each segment needs a separate representation [10].

User complaints. Given the online presence of firms, users have numerous ways to lodge complaints with organizations. These include emails, written reclamation letters, and public rants in social media. Increase in digital user service channels has decreased the barrier of users contacting firms – rather than relying on letters, users nowadays contact firms often via social media direct messages. Managing online complaints effectively is a critical aspect of successful understanding of “what went wrong” in order to improve product and service design [21]. Therefore, user complaints and reclamations provide valuable raw material for requirements engineering and should be collected in a central database [8, 14].

User-generated content and social media. The rise of social media has resulted in a proliferation of unstructured textual data. This user-generated content (UGC) includes text messages, opinions, videos, tweets, emails, posts and blogs created by ordinary people expressing their opinions and exchanging information about products and services with others [23]–[27]. The growth in UGC has motivated researchers to find novel ways to conduct computational linguistic analysis, NLP, and text analytics for user needs detection [6, 26, 33, 52, 60, 62]. NLP can broadly be defined as any kind of computer manipulation of natural language, like speech and text. Text analytics refers to drawing meaning from unstructured text documents. Later sections discuss these methods in greater detail.

Online reviews. User reviews are a form of UGC found at ecommerce sites, such as Amazon, Etsy, or Best Buy. They provide a rich source of text-based information that reflect users’ impressions and experiences on using a product [24, 33, 57, 62, 6]. The large volume of product reviews makes it difficult for researchers to use manual data analysis methods. Automated methods that mine online reviews and extract information are therefore preferred. Although online reviews are a form of UGC, their main difference to other forms of UGC is that they explicitly target a specific product or service. Therefore, their collection and analysis might be more straightforward than user opinions expressed in sporadic contexts (i.e., in random discussions).

From this conceptual overview, we can deduce that user needs detection is a cross-disciplinary activity, with major contributions from computer science, HCI, and marketing.

III. Manual User Needs Detection

A. Approaches in Literature

Researchers use manual methods either solely or in combination with automated methods to analyze user needs data. Manual methods typically involve engagement with users, either on-site where products are used or in another location. The following manual methods for user needs detection are predominantly used:

- *Interviews* rely on open-ended questions to capture answers that reflect user’s sentiments about a product or service [22], [32], [33]. Interviewers may probe users’ remarks to encourage elaboration or to surface latent needs [10]. Sample size varies across studies, depending on a project’s purpose and resources. However, the literature does recommend strategies to obtain the full range of user needs. Griffin and Hauser [10] suggest that having one-hour interviews with 20-30 participants can elicit 90-95% of user needs. While some studies may include more than 30 participants, extensive interviewing tends to yield diminishing returns [10].
- *Observation* can involve active participation with users or detached examination of user practices. This approach is concerned with what people do rather than what they say about their needs. As such, it does not require users’ conscious awareness of their needs in order to capture them [22], [34], [35]. Ethnography, a form of observation, involves deep immersion in a natural setting (e.g., supermarkets, hospitals, offices,

classrooms) to better understand user practices and behaviors in real life situations [22], [36].

- *Focus groups* bring users together to discuss user topics and are valuable because they capture multiple user perspectives at one point-in-time [10], [37]. Discussions are guided by facilitators who typically follow a script but also probe participants for deeper answers. Focus groups may be watched by unseen observers who take notes on the proceedings.
- *Surveys* [28] use different probability sampling methods. Typically, researchers invite users to respond to open or close-ended questions, using Likert scales or any other means of categorization. Data analysis is performed using statistical techniques, such as conjoint analysis [38].

Schaffhausen and Kowaleski [22] used open-ended surveys to devise a needfinding method that could obtain input from large groups in order to inform product development. In a series of online experiments, the researchers provided participants with stimulus information to help them express their needs, via statements or storytelling, related to topics on cooking, cleaning, and housekeeping. Participants were recruited from Amazon Mechanical Turk, a crowdsourcing platform. The study showed that in the equivalent of one day of ethnographic research, a crowd-based method could generate 1,500 need statements and 1,100 stories.

Einwiller and Steilen [23] used (manual) content analysis to evaluate online complaints and corporate response strategies. The researchers coded Facebook comments and tweets and then developed conceptual categories and themes for qualitative analysis. They concluded that company responses to complaints were insufficient. In fact, organizations sometimes tried to divert user complaints away from social media sites in order to keep problems from public viewing.

Intille et al. [39], inspired by photographic and video analysis, proposed image-based experience sampling, an approach to aid users learn more about their own preferences and, through this process, reflect the meanings in their needs. Finally, Timoshenko [20] conducted a study on user needs and oral care products using VOC interviews and ML. He compared results from both approaches and found that the automated method, using UGC, identified more user needs. Rather than rejecting manual techniques completely, Timoshenko proposed an approach for identifying user needs based on a combination of ML and human discernment.

B. *Challenges of Manual Methods*

The literature discussed a broad range of challenges associated with manual methods. We enumerate the challenges of manual methods with the "A" identifier. The main challenges include the following:

- *A01: Limited sample sizes.* While qualitative methods such as in-depth interviewing can capture explicit and latent needs, they rely on small sample sizes, limiting generalizability to other populations (although Griffin and Hauser suggest restricting the number of interviews to achieve needfinding aims). Schaffhausen and Kowalewski's [22] study focused on developing a method to rapidly gather user needs from large groups [22]. The researchers argue that a large-scale needfinding approach would be useful since "uncovering a unique need can be a rare event and a higher quantity of attempts would have a higher likelihood of a rare event occurring" (p. 1).
- *A02: Budgetary constraints.* Gathering and processing data, especially in qualitative research, is an expensive task [22], [40]. It requires subject-matter experts at all stages of the research process, from instrument design to data analysis. Depending on an organization's resources, manual approaches may or may not be feasible or cost-effective.
- *A03: Time constraints.* Qualitative methods are labor intensive and time-consuming. They may require weeks in the field observing behavior or interacting with participants. Qualitative data analysis, is also equally time intensive, since it is largely a manual process, requiring the researcher to closely read, code and interpret data [22], [40].
- *A04: Lack of scalability.* Qualitative assessment of large amounts of data is an overwhelming task. Thus, given its size, UGC and other large datasets tends to be more suited to automated methods of analysis.
- *A05: Difficulty of needs articulation.* Wang et al.[31] note that manual research methods depend on users' "willingness and ability to explicitly express their needs within a well-defined format" (p. 145). Yet, as they observe, some users experience difficulties communicating their intents and preferences to other people. For example, users sometimes use vague or confusing language to describe their needs, making interpretation difficult. Higher level needs are especially hard for users to express [41]. Poor communication during interviews or other interactive approaches may result in misunderstandings [31]. While some methods exist to help designers recognize users' needs [8], there is still lack of rigorously tested methods that help users express their needs more clearly [22].
- *A06: Human bias.* There are several ways in which bias can affect qualitative and quantitative results. For example, qualitative research is at risk for researcher bias (e.g., over-identification with research participants or pre-existing beliefs), which can threaten objectivity and compromise results [31], [42], [43].

IV. AUTOMATED METHODS

A. *Approaches in Literature*

In most cases, researchers remarked that while manual methods remained the "stalwarts and toolbox" of the user needs researcher, automated methods are gaining prominence. The rapid expansion of UGC has spurred novel approaches to collecting and analyzing user needs data. Not only are automated methods adept at handling large volume linguistic datasets, but they are efficient at managing different kinds of data (e.g. structured and unstructured) as well as the real-time speed at which UGC is generated [44], [45]. ML tools and techniques provide the foundation for digital text analysis.

A range of automated methods are applied in the literature. Terms often used interchangeably include text analytics/text mining/topic mining/text analysis [3], [21], [27], [29], [30], automatic text classification [27], [28], [40], [46], sentiment analysis [3], [19], case analogical reasoning [19], latent semantic indexing [21] and deep learning [20], [31]. ML employs algorithms that detect and display patterns in language and then generalize those pattens to make predictions [26], [47]. The algorithms work by building a model from inputs to make data-driven judgments rather than adhering to stringent and static instructions. There are broadly two kinds of models: (a) supervised ML involves manual labeling of training data which is used to teach a system to recognize patterns. In (b) unsupervised ML, no data is labelled, and algorithms are applied to identify and present data patterns [40].

Automated data collection methods offer advantages, such as the ability to aggregate large amounts of text. Compared to manual methods, ML approaches are, in some cases, impartial (i.e., they make comparisons between groups without preconditions) and less likely to introduce human bias into the analytic process. However, bias is still present when humans annotate the training data for supervised ML. Also, different forms of algorithmic bias have been observed [48]–[50]. An interesting aspect is that automated text analysis may be able to detect relationships (or the lack thereof) between texts that humans are unable to see [26].

By quantifying constructs in the text, automated methods may also enable new ways of combining and presenting data [26]. For example, Lee and Bradlow [30] used text mining techniques to process the text from online camera reviews and identify product attributes and attribute dimensions among brands and market segments. They combined these insights with manual user research approaches, such as the VOC. By comparing user reviews to expert reviews, the researchers determined that the two groups valued different camera features. They also found that user segments used distinct vocabularies to describe the same attributes. The researchers suggest that these nuances in vocabulary may help identify subsegments of users and inform user-centered strategies.

Wang et al. [31] drew on deep learning to improve upon conventional methods (e.g. interviews combined with VOC) for mapping user needs onto product design. Deep learning involves teaching models using large sets of training data and layered algorithms. The researchers conducted their research to eliminate communication difficulties during user needs interviews. Ultimately, they successfully mapped keywords to product design parameters, using ML classifiers.

Zhou et al. [3] combined ML techniques, including sentiment analysis, to examine online product reviews within a product ecosystem (Amazon). Sentiment analysis identifies user attitudes towards products by assessing who is speaking, what product/service they are talking about and whether comments are negative or positive. The researchers first used two ML techniques (FastText and the LDA topic model) to filter out the text's noise and extract and generate topics related to user needs. They then used sentiment analysis to understand user preferences quantitatively within the ecosystem by recognizing sentiment and predicting the intensity of the sentiment. By aggregating the number of positive reviews and negative reviews and their intensity levels within a topic, Zhou et al. were able to predict user satisfaction or dissatisfaction.

Wang et al. [51] investigated issue-tracking systems in open-source software communities, and proposed ArguLens, an automated system for consolidating community opinions on usability issues. The system draws from content analysis, used for training data creation, and supervised ML for the extraction of user needs and related opinions. Finally, Nass et al. [52] proposed a method for eliciting user needs and ideas for user experience (UX) improvements, and described the application of the method in a German-speaking call-center.

B. Challenges of Automated Methods

Overall, researchers tend to be enthusiastic and optimistic about the potential of automated methods to produce rich insights from UGC in less time and at lower cost than manual approaches [20], [28], [31], [53]. As Timoshenko [20] notes, "if UGC can be mined for user needs, UGC has the potential to identify as many, or perhaps more, user needs than direct user interviews and do so more quickly with lower cost" (p. 4). With faster and broader user insights, researchers envisioned improvements in product innovation, user satisfaction, and sales growth. Despite the argued advantages of automated methods, the literature also discusses several of their challenges. We enumerate the challenges of automated methods with the "B" identifier. Among others, these include:

- *B01: Inadequate datasets.* Many ML algorithms, particularly those in supervised ML, require large amounts of data before they generate usable results. In their study, Kuhl et al. [40] sought to circumvent this process by using unsupervised ML to quantify user needs. Yet, their testing of multiple unsupervised clustering possibilities did not yield results that made semantic sense. Consequently, they concluded that their dataset was insufficient for an unsupervised approach and devised a process for supervised ML instead.

- *B02: Irrelevant information.* Working with prodigious amounts of unstructured data tends to involve an extensive amount of irrelevant or uninformative samples. For example, online product reviews may contain comments that do not address specific needs. This noise needs to be removed, and pertinent information needs to be extracted, before the data is input into the system by the researchers [3], [31], [54].

- *B03: Lack of informativeness.* Manual methods often produce lengthy transcripts or other forms of text data that enable a rounded analysis of user needs. By contrast, microtext-UGC (e.g., tweets) consists of short sentences and phrases that may not provide enough context for ML or human analysis, particularly for in-depth understanding.

- *B04: Social desirability bias.* Automated text analysis often samples publicly available data in the form of tweets, Facebook postings, online reviews or other UGC. Because these data are public, users may not feel comfortable sharing information that they feel is socially unacceptable or undesirable. In some cases, this information may be relevant to data analysis, and its absence may skew research findings [26].

- *B05: Lack of standards.* Humphreys and Wang [26] argue that there is no standard set of methods, steps of inclusion and exclusion, sampling and dictionary development and validation in automatic text analysis of UGC. They also suggest that the failure to integrate linguistic theory into automated text analysis limits the field and prevents knowledge about "the multiple dimensions of language that can be used to measure user, thought, interaction and culture" (p. 1275).

- *B06: Lack of applicability.* There are some situations when observation of behavior is the only way to study a phenomenon. For example, automated methods, conducted remotely, cannot capture how users interact tactilely with products or navigate space in user environments [26].
- *B07: Inability to determine meaning.* There are circumstances where text analysis would be helpful, but automated text analysis is unsatisfactory. For example, it is impossible for automated methods to detect tone or meaning (e.g., sarcasm, jokes or exaggerations) or make distinctions between argumentation styles or complex concepts. Often, researchers use strategies, such as content analysis [55], [56] and discourse analysis [57] to surface deep, embedded and context-dependent meanings people ascribe to usage practices. Automated processes cannot capture this kind of rich, socially-situated data [26].
- *B08: Need for human involvement.* Claims that ML is significantly less time and labor-intensive than manual methods may underestimate the amount of work these methods require. To function, automated methods demand human-labelled inputs before algorithms in supervised ML can be trained [3]. Researcher involvement, through design, modification, and interpretation, may be necessary at other points too, such as dictionary development and validation. In some cases, manual assessment of the data is necessary after the automatic methods are completed.

V. Discussion

A. *Theoretical Implications*

User needs detection informs requirements engineering of the drivers of user satisfaction and can thus offer profound understanding of why people use products. Our analysis provides implications for research and practice of user needs detection, which is a crucial step in the requirements engineering process.

Regarding the manual methods, *CHALLENGES A01* and *A04-06* can be understood as human limitations regarding data collection and analysis, mainly stemming from lack of scalability and numerical objectivity. *CHALLENGES A02-03*, in turn, relate to organizational limitations – i.e., the results would be needed "now," but are available only after the cumbersome manual research process.

Regarding the automated methods, *CHALLENGES B01-04* relate to data availability and quality. The adage 'quality versus quantity' is extremely pertinent to text analytics. If the original data are poor in quality, then a ML model will not perform well ("garbage in, garbage out"). *CHALLENGES B05-08* relate to methodological limitations of automation – namely the lack of algorithms' ability to truly understand people in a way that produces meaningful insights for design and engineering. Due to the novelty of the methods, the application of automation to user needs detection still remains partially undeveloped, at least relative to manual methods that have been applied for decades. The current challenges of automation deal with data availability and quality, as well as machines' limited capability to understand its content that is deeply embedded in the human condition. Indeed, the lack of general artificial intelligence, capturing social sensibilities and nuances in user needs solely via automatic methods seems like a far cry. Therefore, whether being included in the data annotation process, setting hyperparameters for algorithms, or interpreting the results, the need for humans does not disappear. User needs detection involves a non-trivial amount of interpretative and subjective elements that cannot be outsourced to algorithms. Therefore, automation is to be seen as a helper or enabler, but not as the analyst itself.

Interestingly, not all the challenges are proprietary for a specific type of user detection methods, but some touch both the manual and the automated methods, as shown in Table 1. Namely, "limited sample sizes" (A01) and "inadequate datasets" (B01) refer to the same thing – unavailability of data. Similarly, "budgetary constraints" (A02) can emerge both for manual and automated projects, depending on the resources and capabilities in the organization. "Difficulty of describing needs" (A05) applies also to automated methods; when the source data lacks insights, automation cannot infer them. Symmetrically, this applies to "social desirability bias" (B04) as well – in. "Human bias" (A06) can also exist when using automated methods, as these methods do not work in isolation but require configuration from human developers, thereby being subject to human bias as well.

TABLE I. Uniqueness of the challenges. M = applies to manual methods, U = applies to automated methods, O = applies to both.

A01	A02	A03	A04	A05	A06	B01	B02	B03	B04	B05	B06	B07	B08
O	O	M	M	O	O	O	U	U	O	U	U	U	O

Therefore, even though literature highlights different aspects as strengths and weaknesses, automated and manual methods share much more traits than traditionally perceived. This is perhaps due to the fact that most typically, user detection tasks involve inputs from both humans and systems. As such, the division to "automated" and "manual" might be illusionary, as neither exists in pure form in reality.

With increasing data availability, many researchers expect that AI-based approaches would spread quickly, unlocking important insights for new product and service development [4]. As Lee and Bradlow [30] note, "the radical changes resulting from the Internet and user-generated media promise to fundamentally alter the data and collection methods used to perform these [user need discovery] methods" (p. 881).

However, relying solely on AI, ML, or NLP for user needs detection is not a feasible strategy at this time because of the challenges we discussed in this work. These challenges limit the applicability of AI for user needs detection and, at the same time, offer a clear prescription of "things to improve" for future research in requirements engineering and related domains. The challenges we discussed are not particularly novel (especially those for NLP are well-known [7]), but they nonetheless remain to be solved for the efficient user needs detection. In addition, collaborative tools for user needs detection are needed, enabling human analysts to work in collaboration with ML algorithms and other systems to analyze and interpret large unstructured datasets that potentially contain useful insights for requirements engineering.

B. Practical Guidelines

Our specific recommendations to requirements engineering include the following:

Collect user feedback into central database. As data sources for garnering information on user needs have rapidly expanded beyond internal user feedback to social media and other unstructured UGC, there is a major need to collect data from multiple sources and centralize this data for efficient analysis of user needs.

Monitor the indirect opinions of the users in the product category. This implies not only focusing on user feedback for the given organization, but on feedback provided about rivals and complementary products to better understand user needs in a holistic sense.

Infer both observable and latent needs. Major efforts should be put towards going beyond the visible textual needs to understand the underlying drivers of behavior – this requires creating user needs taxonomies with hierarchical levels of abstraction.

Corroborate your findings with real users. To avoid echo chambers and misconceptions, it is crucial to verify user requirements after the first round of analysis. This can be done by applying the Delphi logic [58] – i.e., asking users to confirm whether we understood their needs correctly.

Centralize user needs into an easy-to-understand representation. This can be done by grouping user needs into one humanized representation – a persona [59], [60]. Creating personas may enhance the empathetic understanding of users [61], [62].

Prioritize user needs. Depending on the data volume, user needs detection could result in hundreds of unique needs. Therefore, it is important to measure the severity and frequency of each need, and then prioritize the needs for development.

Do not outsource creativity to users**.** Finally, it is crucial to not rely solely on user feedback for new feature development. Developers should not presume that users know how to solve a given problem. Instead, user needs detection is about learning of users' needs towards identifying problems. Solving these problems requires creative engineering efforts that should be further tested among real users in the frame of agile development.

VI. Conclusion

We discussed methods for user needs detection, identifying six main challenges with manual methods and eight main challenges with automated methods; many of which are shared. Despite the promise and hype of automated methods, the several identified challenges suggest that automation is not (at least yet) mature enough to replace manual methods for requirements engineering. We further provide actionable recommendations for researchers and practitioners alike on how and when to use automated and manual methods for detecting user needs towards creating better products and services.

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