RESEARCH ARTICLE

Methodological considerations on the means-end chain analysis revisited

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Abstract

Means-end chain analysis has been applied in a wide range of disciplines to understand consumer behavior. Despite its widespread acceptance there is no standardized method to analyze data. The effects of different analyses on the results are largely unknown. This paper makes a contribution to the methodological debate by comparing different ways to analyze means-end chain data. We find that (1) a construct that is not mentioned can still be important to a respondent; (2) coding constructs at the same basic level or condensing constructs at a superordinate level lead to different results and both an increase and decrease of information; (3) aggregating data can be based on different algorithms which influences the results. Among available software packages there is no consistency in the used algorithm; (4) before applying means-end chain analysis in a new research area the validity of assumptions underlying the research model should be evaluated. We conclude there is no universal "best way" to means-end chain analysis, the most suitable approach depends on the research question. Research concerning how products are evaluated can best apply number-of-respondents-based aggregation and low levels of condensation. Research concerning why products are valued can best apply frequency-of-responses-based aggregation and high levels of condensation.

KEYWORDS
assumptions, consumer decision making, laddering, personal construct theory, research context, research method

1 | INTRODUCTION

The means-end chain model and related laddering methodology were developed in the 1980s to understand not only how, but also why, consumers value products or services (Grunert & Grunert, 1995; Gutman, 1982; Reynolds & Gutman, 1988). Since its development, the method has been widely used to gain insight into consumers' product knowledge and motives for product choice (Anastasiadis & van Dam, 2014; Costa et al., 2007; Merfeld et al., 2019; Reynolds &

Phillips, 2009). Means-end chain theory is based on several influential theories in psychology (Reynolds & Olson, 2001), such as personal construct theory (Kelly, 1955), attribute theory and cognitive structure (Scott, 1969), and human values (Rokeach, 1973). Means-end chain analysis allows marketing problems to be framed and analyzed as consumer decisions. In means-end chain analysis, qualitative data are transformed into quantitative results which tends to have high levels of appeal for marketing research. Consequently many applications of means-end chain analysis are found in market research covering product

development and evaluation (Costa et al., 2004; Patrick & Xu, 2018; Reynolds & Phillips, 2009), advertising (Bech-Larsen, 2001; Eberhard, 2017), and market segmentation (Grunert, 2019; Pezeshki et al., 2019; Ter Hofstede et al., 1999).

Means-end chain analysis is an umbrella term for several related methodological parts. In combination with its application in several research fields, this has resulted in haphazard development of its theoretical and methodological underpinnings (Grunert et al., 2001; Reynolds & Olson, 2001). Numerous methodological papers have appeared that focus on specific aspects of means-end chain analysis such as the merits of different attribute elicitation techniques (e.g., Bech-Larsen & Nielsen, 1999; Steenkamp & Van Trijp, 1997), the differences between hard and soft laddering (e.g., Grunert & Grunert, 1995; Phillips & Reynolds, 2009; Ter Hofstede et al., 1998), the determination of a suitable cut-off level (e.g., Bagozzi & Dabholkar, 1994; Grunert & Grunert, 1995; Reynolds & Gutman, 2001), different techniques to analyze and report the aggregated results (e.g., Aurifeille & Valette-Florence, 1995; Fu & Wu, 2013; Gengler et al., 1995; Kaciak & Cullen, 2006; Leppard et al., 2003; Ter Hofstede et al., 1998; Valette-Florence & Rapacchi, 1991), or the interpretation of the results (e.g., Grunert & Grunert, 1995; Olson & Reynolds, 2001). These explorations of specific methodological aspects have not resulted in a complete and formalized means-end theory that supports a single methodology (Olson & Reynolds, 2001; van Rekom & Wierenga, 2007). As a result, the means-end approach lacks a clearly specified theoretical foundation, limiting its appeal to academic scholars in consumer research (Grunert, 2010; Reynolds & Olson, 2001).

Despite the lack of a clear theoretical foundation, application of means-end chain analysis has spread to new domains since the turn of the century. Examples are tourism, agriculture, and user experience studies (e.g., Klenosky, 2002; Lagerkvist et al., 2012; Vanden Abeele et al., 2012). This application of means-end chain analysis in new research areas is generating novel methodological complications. For example, in user experience studies less elaborated ladders that contain comparatively more attributes and less values are typically elicited, which requires a tailored analysis (Vanden Abeele & Zaman, 2009; Vanden Abeele et al., 2012). LADDERUX software was developed to improve the reliability and validity of means-end chain analysis for these user experience studies.

In this paper, we will address methodological difficulties that were encountered while applying means-end chain analysis in a smallholder context in Uganda. The findings of this study contribute to the theoretical understanding of means-end chain analysis and consumer psychology in general, as well as the identification of methodological implications when applied among smallholder farmers. We will start with a brief overview of the method and the debates around its different steps. Thereafter we will make a contribution to the debate based on application of means-end chain analysis to understand smallholder farmers' decision making. We analyze in detail a case study conducted among Ugandan banana farmers, and in addition draw upon literature of other studies conducted among smallholder farmers aiming to understand their choices on seed selection. The results and discussion focus on 4 main issues:

1. Attribute elicitation and why important attributes might not be elicited.
2. Coding and the difference between coding and condensing.
3. Aggregating results and the difference between algorithms based on frequency-of-responses and algorithms based on number-of-respondents.
4. Application in a new research area and methodological considerations.

1.1 | Means-end chain analysis

Means-end chain analysis refers to a set of techniques for interviewing individual consumers about the reasons for their product choice and interpreting consumers' responses in terms of generalizable linkages between outcomes (Olson & Reynolds, 2001). Means-end chain analysis is firmly based in the pragmatic and functionalist marketing tradition (Alderson, 1957; Brown, 2002; Dixon & Wilkinson, 1984). This tradition builds on the assumption that all people construct a mental representation for making sense of and acting upon the world they experience (Brunswik, 1943; Kelly, 1955). This personal mental representation consists of a web of functional associations and informal hypotheses that predict personally relevant consequences from observable cues (Neisser, 1976; Peirce, 1878; Tolman & Brunswik, 1935). In this web of constructs the products that people purchase are bundles of functionalities that they can use (Lancaster, 1966; Rosen, 1974). People prefer and select products for the consequences that these products (are expected to) provide, and for the goals that these consequences help to achieve (Vargo & Lusch, 2004). Because people have different skills and aptitudes, and because people live in different circumstances and contexts, they perceive different relations between observed attributes, inferred consequences, and valued goals (Jan et al., 2012; Peach & Constantin, 1972; Storkerson, 2010; Tolman & Brunswik, 1935; Zimmermann, 1933). Means-end chain analysis accommodates these individual differences by inviting individual respondents to select and verbalize their own constructs to describe how products are linked to their personal goals (Walker & Olson, 1991).

Beyond the domain of consumer marketing means-end chain analysis has been applied to, for example, business research (Inoue et al., 2017), organizational research (Bourne & Jenkins, 2005; Ronda et al., 2018), and project management (Verburg et al., 2013). Recently means-end chain analysis is also recognized as a promising tool to better understand farmers' motivations for the adoption or nonadoption of novel agricultural practices or technologies (e.g., Lagerkvist et al., 2012; Ngigi et al., 2018; Okello et al., 2019; Salame et al., 2016; Urrea-Hernandez et al., 2016). In these different applications the core purpose of the analysis has remained unchanged over time: to explore the implicit product knowledge and personal motives of respondents that explain the choice for one course of action over another. This notwithstanding in any study each individual laddering interview only can cover part of each respondent's cognitive or motivational web of sense-making (Grunert & Grunert, 1995). To generate a valid shared web of sense-making the

results of laddering interviews therefore have to be aggregated across respondents.

1.2 | Collection and aggregation of means-end chain data

A means-end chain analysis starts with the elicitation of personally relevant attributes that a respondent uses to evaluate a product or service. Starting from these elicited attributes individual interviews uncover the relations between the (physical) features and attributes of products and their (psychologically) valued consequences (Reynolds & Gutman, 1988; Reynolds & Phillips, 2009). This is done by repeatedly asking the respondent "why is it important to you that…" which results in a personally relevant sequence of attributes, consequences, and values referred to as "ladders." These interviews, commonly referred to as laddering interviews, cover each elicited attribute of the respondent.

Once the data have been collected for individual respondents, the analysis follows three steps (Aurifeille & Valette-Florence, 1995; Gengler et al., 1995; Grunert & Grunert, 1995; Reynolds & Gutman, 1988). First, a content analysis is performed and comparable constructs of individual ladders are coded into common denominators. Second, the linkages between coded constructs in the ladders are aggregated across respondents in an implication matrix. Third, the aggregated associations between attributes, consequences, and values are represented graphically in a hierarchical value map. This hierarchical value map is made comprehensible and readable by deleting incidental and redundant linkages, allowing a focus on the dominant means-end chains. The distinction between "dominant" and "incidental" is determined by the researcher by selecting a cut-off level. Linkages that occur less than the selected cut-off level are not presented in the hierarchical value map.

In the aggregated hierarchical value map the dominance of a specific means-end chain should depend on a frequency and a representativeness criterion, i.e. the number of individual ladders that are represented by that chain and the accuracy of that representation (Aurifeille & Valette-Florence, 1995). Among the three steps coding is the most cumbersome, and iterative coding may be required before a satisfactory balance between representativeness and manageability is achieved (Grunert et al., 2001). Once the coding has been performed, the actual aggregation is usually considered uncomplicated but time consuming. Therefore several computer software programs have been developed, like LADDERUX, MECANALYST, or LADDERMAP, that transform ladders into hierarchical value maps (Lastovicka, 1995; Naspetti & Zanoli, 2004; Vanden Abeele et al., 2012).

2 | METHOD

A means-end chain analysis was conducted among Ugandan farmers to understand choice for supplier of banana planting material. Data were collected in interviews with 31 banana farmers during November, 2017. Apart from collecting demographic and production information, the interviews consisted of two parts: attribute elicitation and laddering. Data were collected by five interviewers who had received a two-day training to conduct the interviews.

2.1 | Attribute elicitation

Attributes were elicited by triadic sorting following the repertory grid method (Kelly, 1955). The respondents (farmers) were presented with triplets of cards, with a different source for banana planting material written on each. In total nine different sources for banana planting material were offered, representing a range of formal and informal channels: a laboratory, a nursery, the National Agricultural Advisory Services (NAADS), the National Agricultural Research Organisation (NARO), a Non-Governmental Organisation (NGO), a large-scale farmer, a remote farmer, a neighbor and the own farm. Each respondent was presented with nine pre-defined triplets of cards. For each triplet of cards respondents were asked to group two sources which appear similar to them as opposed to the other. While doing so the respondents were given the following scenario:

> Imagine you have to source banana planting material for the coming planting season. I now present you with three seed sources where you could source this planting material. Which two seed sources have, according to you, more similarities as opposed to the other?

After grouping a triplet of seed sources each respondent was asked to describe why these two where similar compared with the other one. This was repeated for each triplet, resulting in a list of bi-polar word pairs. Next the bi-polar word pairs were listed, and for each word pair the respondent was asked which of the two was preferred. This resulted in a list of preferred "constructs" and non-preferred "contrasts."

2.2 | Laddering

The soft laddering method (Grunert & Grunert, 1995) was used to elicit individual means-end chains using the elicited constructs as starting attributes. Soft laddering is the recommended technique in studies with a relatively small sample size (<50) and of an exploratory nature (Costa et al., 2004). Starting from each preferred construct a series of "Why is it important to you that…" questions were asked until the respondent reached a dead end. Means-end chain theory postulates that in this asking a ladder of constructs is created. If more than one reason for importance was given to a construct, each of these were explored further and a forked ladder of constructs was created. It was emphasized to

the respondents that there were no right or wrong answers and that the aim of the interview was to understand their individual preferences.

2.3 | Coding

After conducting all the interviews, the constructs mentioned in the ladders were coded. Coding was done by two researchers independently. In cases of inconsistencies, the team discussed which code was most suitable using transcripts of the original interviews. The main purpose of coding is to enable aggregation of responses across individual respondents, but guidelines for this aggregation are notoriously vague. Coding should be broad enough to obtain replications "across more than one respondent" but not so broad as to lose "too much" meaning (Reynolds & Gutman, 1988). To compare the effect of "the level of condensation" on the results, contrasting constructs (e.g., "dark peel" and "light peel") were both grouped, and not grouped, into a superordinate construct (e.g., "peel color").

2.4 | Constructing the hierarchical value map

After coding an implication matrix was constructed to create means-end chains by aggregating the ladders across all respondents. From the implication matrix, a hierarchical value map was created to graphically present these aggregated means-end chains. For the construction of the implication matrix and hierarchical value map two algorithms were used. The first algorithm aggregated the frequency (f) of direct and indirect linkages between constructs to arrive at the implication matrix. If the same respondent repeated a linkage between the same two constructs in different ladders, each appearance of this linkage was counted in the implication matrix. The second algorithm aggregated the number-of-respondents (n) making direct and indirect linkages between constructs to arrive at the implication matrix. If the same respondent made a linkage between two constructs multiple times, the linkage was only counted once in the implication matrix. Both algorithms are commonly used in existing research.

The cut-off levels to be used for the construction of the Hierarchical Value Map (HVM) should create an informative but clear picture (Reynolds & Gutman, 1988). A more formalized way of deciding on a cut-off level has so far not been agreed upon in literature (Costa et al., 2004). For the comparison of the two algorithms the cut-off levels were chosen in two different ways. First the cut-of level of the frequency-based hierarchical value map (f-HVM) and the number of respondent-based hierarchical vale map (n-HVM) were chosen to represent approximately the same percentage of the total established linkages. Next the cut-off level of the n-HVM was set at the same absolute value as the f-HVM.

3 | RESULTS AND DISCUSSION

3.1 | Why attributes are elicited or not

Attribute elicitation, for which several methods are available, forms the basis of means-end chain analysis. Attributes can be classified along three dimensions of importance: salience, relevance, and determinance. Salience reflects the ease at which attributes come to mind, relevance reflects the degree to which an attribute is linked to personal or social values, and determinance reflects the importance of an attribute in judgment and choice (Van Ittersum et al., 2007; van Dam & van Trijp, 2013). Different elicitation techniques lead to different sets of attributes (e.g., Bech-Larsen & Nielsen, 1999; Steenkamp & Van Trijp, 1997; Van Ittersum et al., 2007). In addition to the elicitation technique, attribute elicitation is dependent on the product-use situation (Fransella et al., 2004). The product-use situation modifies the relevance of consequences for that particular situation. Therefore respondents must be provided with a scenario describing the particular product-use situation before starting the elicitation task.

It is known that different elicitation techniques lead to a different set of attributes, and that the product-use situation has an influence on the elicited attributes. This notwithstanding we want to introduce a new consideration on differences in elicited attributes. This consideration is especially relevant when means-end chain analysis is used to compare different groups of consumers, where the method of attribute elicitation and product use situation are kept constant. Means-end chain analysis draws from multiple psychological theories, which means results can be interpreted in multiple ways. A main underlying assumption is that while making choices, consumers create categories based on cognitive distinctions. "Distinctions are dichotomies that represent the end points of dimensions along which objects may be compared" (Gutman, 1982, p. 63). How consumers group products or services in different categories depends on which features they emphasize and ignore (Gutman, 1982).

One concept that means-end chain theory uses to explain those features people use in their evaluation is motivation (Mort & Rose, 2004). Personal values represent an individual's goals, desires, or aspirations and motivate decisions and actions (Okello et al., 2018). The concept of motivation is linked to probabilistic functionalism: behavioral motivation to consume is based on how product knowledge is related to self-knowledge. Attributes are thus selected for the consequences they are expected to provide, that help achieve personal values. Probabilistic functionalism plays a central role in the personal construct theory. The personal construct theory implies that a construct only is convenient for the anticipation of a finite range of events.

The objective of means-end chain analysis is to explore the implicit product knowledge and personal motives of respondents that explain the choice for one course of action over another. But when a certain chain of constructs does not appear, is that due to a lack of motivation, a lack of product knowledge, or because it's not in the

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range of convenience? For example: when the hierarchical value maps of two groups of farmers are compared, the following difference might emerge: group A relates "low pesticide use" to "save money" and "better for health," group B relates "low pesticide use" to "save money" alone. Based on the above named theories, how should these results be interpreted? Based on the concept of motivation, health might be more important for one group providing the motivation to reduce pesticide use. Based on probabilistic functionalism, one group might be aware of the negative side effects on health and reduces pesticide use, whereas the other group is not aware of those negative side effects. And based on the personal construct theories' range corollary, one group of farmers could be organic producers that do not consider the level of pesticides use at all as pesticides are outside their range of convenience.

These different possibilities make interpretation of means-end chain data complicated. Moreover motivations, experiences, and ranges of convenience can change over time. For example, subconscious motivations can be activated by goal priming (Okello et al., 2018). Experience and learning are cyclic, therefore a person's knowledge and believes can constantly be adapted (Kelly, 1955). Ranges of convenience can change based on a person's openness to increase the range (Kelly, 1955), for example when a conventional farmer shifts to organic farming practices. The interpretation that some features are emphasized by one group and ignored by another might thus be too simplistic and can result in misunderstanding. It is important that researchers are aware of these differences when interpretating their data. To make an adequate interpretation, profound understanding of the researched population is essential.

3.2 | Coding and condensing

In means-end chain interviews respondents create ladders using their own verbalizations. Different respondents use different words for similar constructs and this requires coding to enable aggregation of responses across respondents. To be able to aggregate responses, constructs must be coded into common denominators, thereby reducing the number of unique ladders. Responses such as "…will generate a higher yield" and "…will increase the production" can be coded into "increase yield." To a large extent coding determines the outcomes of the research. Propper coding is a most complicated step in means-end chain analysis because of unresolved theoretical issues (Grunert et al., 2001). Broad coding reduces the number of constructs to manageable proportions but result in loss of meaning whereas narrow coding preserves meaning but results in high numbers of constructs that are cut-off and lost afterwards (Grunert et al., 2001; Reynolds & Gutman, 2001). Resolving this methodological conflict requires the consideration of theoretical issues. We discuss three issues regarding coding where means-end chain analysis diverges from the underlying personal construct theory.

One assumption that means-end chain analysis adopted from personal constructs theory is that respondents perceive the world in dichotomies. In means-end chain analysis these dichotomies imply

that perceived distinctions indicate the end points of a dimension along which objects may be compared (Gutman, 1982). When respondents make a dichotomy they are requested to state their preference to one of the end points of this dimension. This preference forms the starting point of the laddering interviews. In personal construct psychology dichotomous perception implies that constructs are bipolar and each construct implies a contrast. Each evaluation simultaneously affirms and denies, because perceiving something implies perceiving something as not its contrast. Often the opposite pole of a personal construct gives us a clear meaning of that construct. This bipolarity does not imply that the underlying dimension is dichotomous, because different pairwise comparisons may imply a range of possible evaluations on a single dimension (Fransella et al., 2004). For example respondents perceive a large-scale farmer to be "located far away" when compared with a neighbor. The same large-scale farmer is perceived "located close by" when compared with a nursery (Kilwinger et al., 2020). "Far away" and "close by" is an axis of reference, so that elements which in one context are "far away," in another context become "close by." Respondents' preferences on such a ranged dimension may be at any ideal point, rather than at one of the end-points (Huber, 1976; Moore, 1982). Both in coding and in the interpretation of aggregated responses it must be clear that a preference in a specific direction does not imply that "more is better" indefinitely.

A second assumption that means-end chain theory adopted from personal constructs theory is that these dichotomous constructs are organized hierarchically. In means-end chain theory the hierarchical ordering implies that all associations express causality, as an attribute causes to a consequence and a consequence causes a value (Grunert et al., 2001). People distinguish between product attributes causing desired and undesired consequences, and the prefer the former. Thus farmers prefer a "round shape" of seed potatoes because round seed potatoes cause a "high yield" (Okello et al., 2018). In personal construct theory the hierarchical order of construct refers to two noncausal types of ordering (Fransella et al., 2004; Mirman et al., 2017). One type of ordering creates an abstraction that transcends the construct-contrast distinction. A subordinate bipolar dimension becomes one end pole of a superordinate dimension. This condenses information taxonomically and logically (Wierzbicka, 1984; Yee, 2019). The construct potato is superordinate to a range of distinct varieties and species, and subordinate to the nightshade family. Likewise the shape of a potato is superordinate to round and oval and subordinate to the appearance of the potato. The other type of ordering creates a clarification by thematic extension within a given context. This enriches information by invoking subjective associative knowledge (Neisser, 1976; Plant & Stanton, 2013; Ratneshwar et al., 2001). Thus new varieties of seed potato from a formal seed developer can be associated with higher yields and a rounder shape compared with traditional varieties.

Now we have described that the hierarchical assumption differs between personal construct theory and means-end chain theory we want to introduce the distinction between coding and condensing. The purpose of coding in means-end chain analysis is to allow

aggregation of responses given in own words by grouping them into a common denominator. This is often confused with what we call condensing which is grouping subordinate constructs into a super-ordinate construct. For example Grunert et al. (2001) state that "tastes great" and "excellent taste" can be coded into "good taste," and that "good taste" and "bad taste" can in turn be coded into "taste." The number of constructs can be reduced by grouping sub-ordinate constructs into a superordinate denominator, but attributes are coded into attributes and consequences into consequences. The superordinate code should also maintain the valence of a construct. The information on how the preferred consequences are related to distinct product attributes is lost when subordinate constructs are condensed into a superordinate construct. Coding (or rather con-densing) should hence maintain the right level of abstraction of a construct.

Grunert et al. (2001) therefore argue that each step that makes coding more "condensed" leads to a loss of information due to in-creased abstractness. This notwithstanding the abstracting hierarchy can provide a more general insight in systemic relations that are independent of personal preferences. This is important if different respondents express a preference for opposing poles of a dimension, or if they use distinct related dimensions, like shape and color, for the same end. Condensed coding for abstraction can show that,

despite individual differences, farmers generally use "appearance" of seed material to evaluate quality (Okello et al., 2018; Urrea-Hernandez et al., 2016).

To illustrate this we condensed our coding by grouping dichot-omous constructs into a superordinate construct, for example, "im-proved cultivar" and "traditional cultivar" into "cultivar type." This reduced the number of concrete attributes presented in the HVM from 10 to 8 but adds two new abstract attributes (Figure 1). The newly appearing constructs relate "cultivar type" to "adaptability to environment" and "disease resistance." This adds information to the value map that adaptability and disease resistance are important to farmers and depend on the cultivar type (Figure 1a). It does not provide the information that apparently there is no consensus among farmers about the type of cultivar that provides these consequences. In addition it does result in a loss of information that "traditional cultivars" are preferred because they have a "good taste" and a "long lifespan," whereas "improved cultivars" are valued because of their "big bunches" (Figure 1b). Condensing subordinate constructs can thus result in both an increase and a loss of information at the same time. This makes it hard to argue which method might be better as this depends on the research question. It is at least important that researchers are aware that "coding" responses given in own words into common denominators is different than "condensing" responses
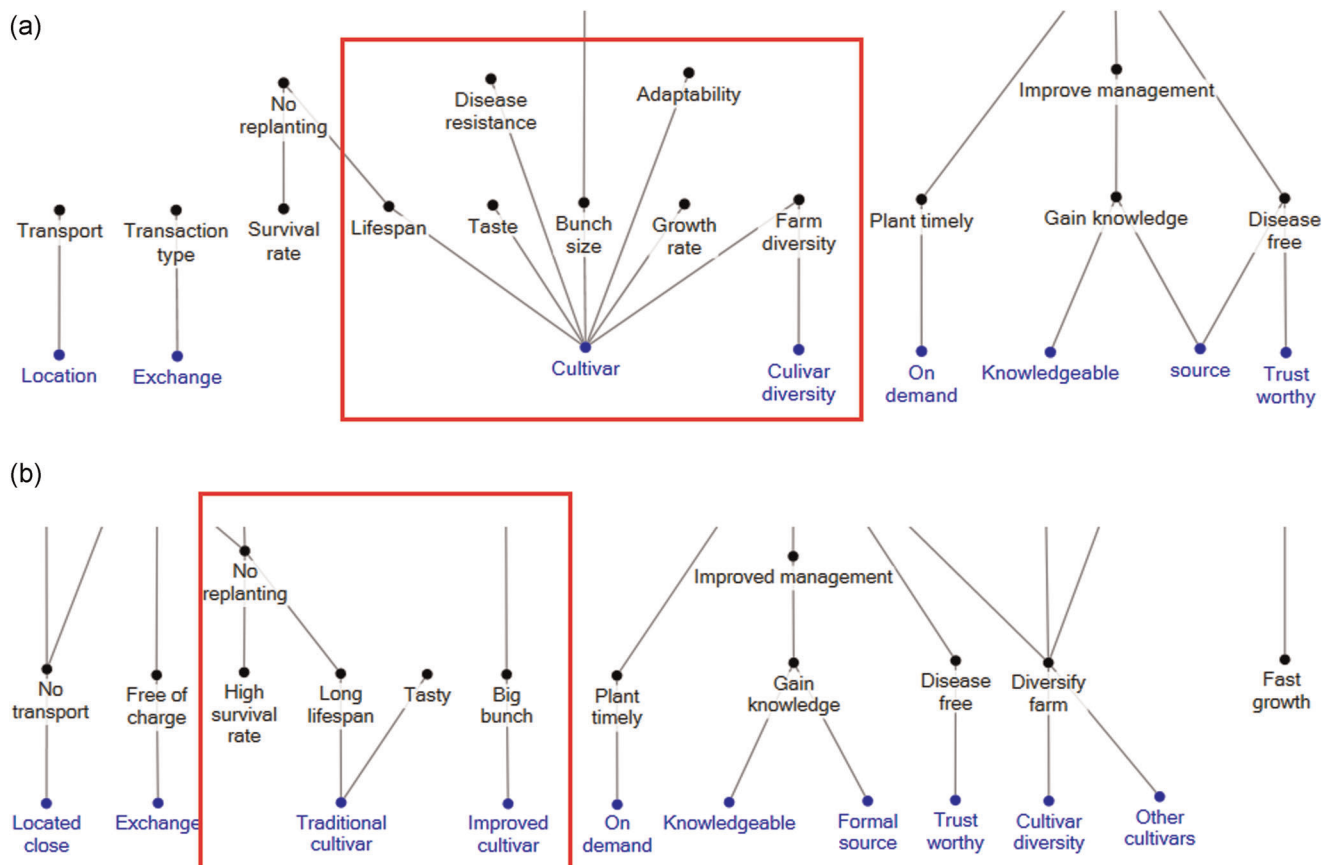

FIGURE 1 Effect of coding by (a) condensing, and (b) not condensing subordinate constructs. Concrete attributes are presented in blue. The red square highlights the effect of condensing the attribute "cultivar" [Color figure can be viewed at wileyonlinelibrary.com]

in a superordinate denominator, know the consequences of condensing on their results, make informed decisions, and apply a consistent level of condensation on their data set. When researchers are not consistent this might lead to a skewed understanding of differences between consumer groups. In sum we have discussed here three issues of coding that have not been described clearly in literature and might be confusing: (a) dichotomous constructs ≠ bipolar constructs, (b) hierarchical relation of constructs ≠ hierarchical order of constructs, (c) coding responses ≠ condensing responses.

Coding and condensing are cumbersome tasks that require expertise and greatly influence the results of the study. To avoid biases, there could be a future role for text analysis software (such as specific R studio packages like "tidytext" or Atlas TI). Such software is capable of systematically analyzing text and can store responses at different levels of "condensation," starting at the original statement to abstract constructs. Further research is needed to explore the accuracy of such software compared with manual coding and condensing.

3.3 | Transforming individual ladders into means-end chains

After all the elicited constructs have been coded, the links between constructs made in the individual ladders can be aggregated in an implication matrix. In this step, the qualitative data is transformed into quantitative data. This implication matrix should display "the number of times each element leads to each other element" (Reynolds & Gutman, 1988). This can be interpreted in several ways. For example, both direct and indirect linkages can be counted in the implication matrix. Another possibility is to count the number of times elements are linked or the number of respondents that link elements. In laddering interviews, the implicit knowledge and understanding of each respondent is made explicit by linking concrete attributes through abstract attributes, functional consequences, psychosocial consequences, and instrumental values to terminal values (Walker & Olson, 1991). Whenever different concrete attributes link to a similar higher level construct, which is likely to happen after coding, all subsequent linkages can be duplicated in the interview. This increases the frequency in which linkages between the (higher level) constructs are mentioned but not the number of respondents who mention them. The number of respondents who mention a linkage across interviews indicates the dominance of the linked constructs, and the representativeness of that linkage, in the population (Valette-Florence & Rapacchi, 1991).

Apart from common linkages that are shared with others, people will have unique individual sets of constructs and linkages due to their individual differences in circumstances, skills, and aptitudes. Counting the *frequencies* of linkages across and within respondents or counting the *numbers* of respondents making the same linkage therefore will lead to different outcomes. Number-of-respondent-based aggregation favors dominance of commonly shared linkages in the population and tends to ignore context-specific individual linkages. Frequency-based aggregation favors individually dominant linkages relative to commonly shared linkages. The study of consumer behavior can historically be divided in two perspectives: the idiographic and nomothetic. The idiographic perspective aims to find explanations for behavior that are individual-specific. The nomothetic perspective aims to find universal principals of behavior across individuals (Bagozzi & Dabholkar, 2000). Frequency-of-responses-based aggregation seems to fit the former perspective and number-of-responses the latter.

Both counting frequencies and number-of-respondents have been converted into algorithms that are commonly used for data aggregation. Among laddering software the program LADDERMAP counts numbers and construes an implication matrix "such that, though a given respondent may repeat the associations between the same cognitions several times in several ladders, the association between cognitions is tabulated only once per subject" (Lastovicka, 1995, p. 495). The software program LADDERUX on the other hand counts frequencies and construes an implication matrix from the frequency with which an association is mentioned across multiple ladders within and across respondents (Vanden Abeele et al., 2012). MECANALYST provides both options and the manual states that: "if a synonym is repeated a number of times in the same subject/ladder, then this can be ignored by selecting "Use single links in same subject/ladder" or taken into account by selecting "Use multiple links in same subject/ladder." Normally, the single links option should be checked for both subject and ladder to prevent the results from being biased by garrulous interviews. But in some instances you may want to choose a different option" ("MECAnalyst user guide," s.d., pp. 31–32).

The choice of algorithm for aggregation will affect the results of a means-end chain analysis in the hierarchical value map. When results are presented with a cut-off level of 1, all linkages are represented by both algorithms, but frequency-based aggregation will give higher weights to linkages that are repeated in a single interview. When results are presented with an absolute cut-off level higher than 1, the number-based aggregation will represent a subset of linkages compared with the frequency-based aggregation, because the latter will also show linkages that are mentioned several times (over cut-off) by a few (under cut-off) respondents. A frequency-based algorithm implies higher numbers of observations for linkages compared with a number-based algorithm and therefore requires a higher cut-off level to maintain readability. Once different cut-off levels are used for number-based and frequency-based aggregation, even if a similar fraction of linkages is represented the resulting hierarchical value maps will no longer overlap. This notwithstanding, the vast majority of research papers do not explain by which algorithm the implication matrix is construed, even if the software used is mentioned, nor whether the aggregated numbers in the implication matrix refer to frequencies of linkages or number of respondents mentioning the linkage.

After coding our own data set a total of 88 constructs remained of which 40 were classified as attributes, 24 as consequences,

TABLE 1 Number of direct linkages that would appear at a cut-off level between 2 and 7 for frequency-based hierarchical value maps (f-HVM) and number-based hierarchical value maps (n-HVM) (n = 31)

Cut-off level	Number of direct linkages f-HVM	% of total directly linked constructs	Number of direct linkages n-HVM	% of total directly linked constructs
1 (total)	420	100	420	100
2	222	53	168	40
3	144	34	90	21
4	109	26	51	12
5	75	18	33	8
6	53	13	24	6
7	42	10	18	4

TABLE 2 The total number of constructs classified as attributes, consequences and values and the number and percentage of constructs appearing in the f-HVM with cut-off level 6 and n-HVM with cut-off level 4. The selected cut-off levels keep the total number of appearing constructs closest to 50% for both algorithms

Constructs	Total	f-HVM (cut-off level 6)		n-HVM (cut-off level 4)	
		n	%	n	%
Attributes	40	10	25	15	38
Consequences	23	21	91	20	87
Personal values	25	15	60	6	24
Constructs total	88	46	52	41	47

and 25 as personal values. The aggregated implication matrix resulted in a total of 420 different direct linkages between 88 constructs (Table 1). Most of these linkages only appeared once (47%) or were made by only one respondent (60%).

To construct the f-HVM a cut-off level of f = 6 (Figure 2) presented a feasible balance between information and interpretation. This resulted in a HVM with 53 direct linkages between constructs, representing approximately 13% of the original linkages in the f-HVM (Table 1). Of the original 88 constructs 46 appear in the f-HVM (52%). Of the constructs that appeared in the f-HVM, 10 were classified as attributes, 21 as consequences, and 15 as personal values (Table 2). To construct a
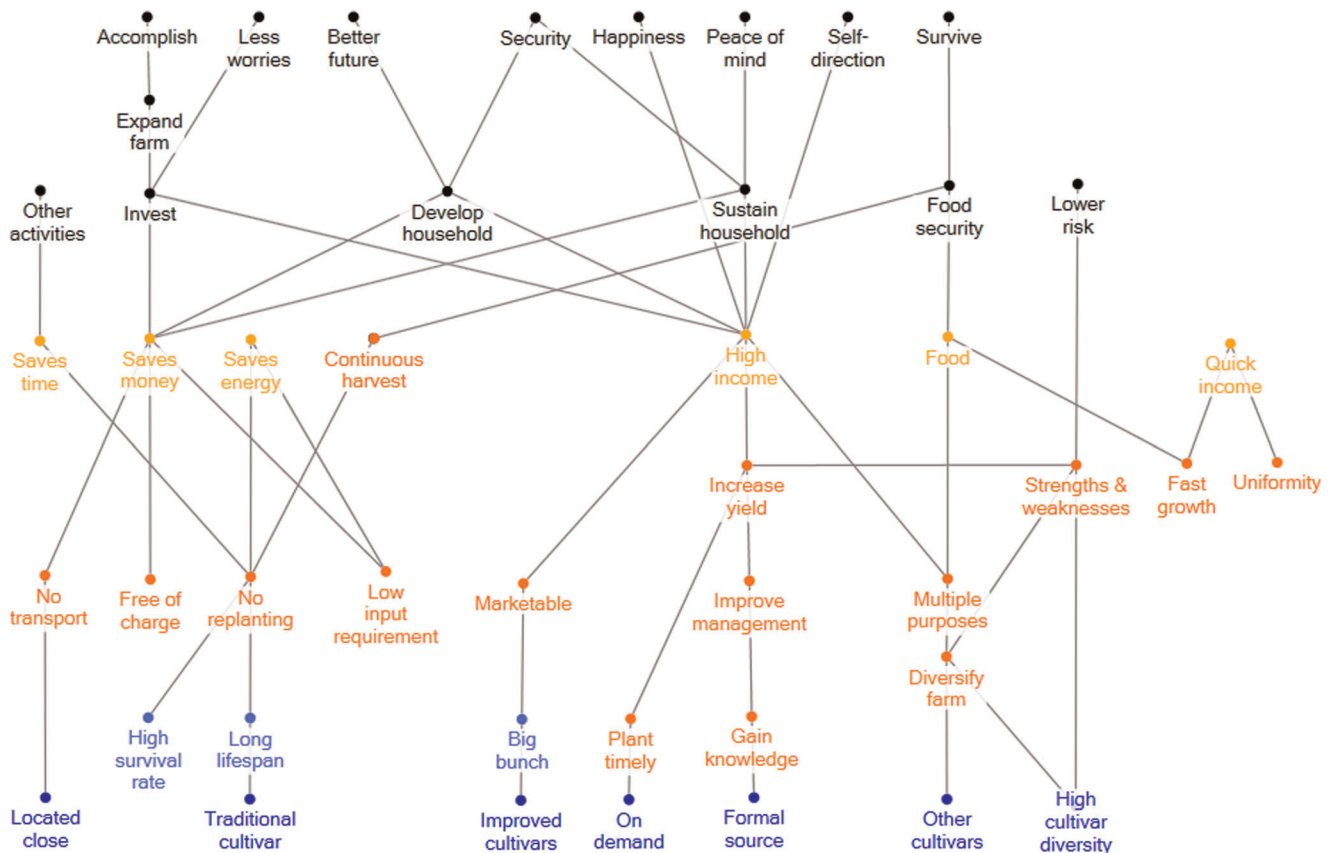

FIGURE 2 Frequency-based (f) hierarchical value map (f-HVM). The hierarchical value map is based on the accumulated frequency of direct linkages between constructs made by the respondents. Attributes are presented in blue, consequences in orange and values in black. n = 31; Cut-off level: f = 6 [Color figure can be viewed at wileyonlinelibrary.com]

comparable n-HVM, a cut-off level of *n* = 4 was used (Figure 3). This cut-off level results in an n-HVM with 51 direct linkages between constructs, representing 12% of the total number of active linkages. In the n-HVM, 41 constructs (47%) appear of which 15 were classified as attributes, 20 as consequences, and 6 as personal values (Table 2). Using the same relative cut-off level (12%–13%), the reproduction of personal values in the *f*-HVM (60%) was much higher compared with the n-HVM (24%); whereas, in contrast, the number of attributes was slightly higher in the n-HVM (38%) compared with the *f*-HVM (25%). In both HVMs almost all the coded consequences were represented (Table 2).

To further understand the effect of the used algorithm on the HVM, an n-HVM was constructed using the same absolute cut-off level (6) as the *f*-HVM (not presented). This n-HVM with cut-off level *n* = 6 showed only 24 direct linkages (6%), which is considerably less than the *f*-HVM with a cut-off level of 6. Also the integrity of the n-HVM is jeopardized at this cut-off level because several means-end chains are only partially reproduced: they either end or start at the level of consequences. From Table 2, it can be seen that construing an *f*-HVM with a cut-off of 4 (like the n-HVM in the previous analysis) would result in an impossible 109 direct linkages (26%).

3.4 | Applying the means-end chain analysis in a new research area

Means-end chain analysis takes different realities of respondents into consideration and therefore increasingly is used to explore farmers' tacit understanding of available resources relative to their goals and aspirations within their technological, ecological, and socio-economical context. Rather than forcing respondents into predetermined categories, the method enables respondents to define personally relevant constructs in their own words. Therefore the method is considered more suitable for research in cross-cultural settings compared with traditional survey approaches (Watkins, 2010). Moreover, the psychological theories on which means-end chain analysis is based have considerable overlap with theories underlying recent approaches to understand technological change in smallholder agriculture, such as the theory of affordance (Gibson & Carmichael, 1966; Glover et al., 2019).

Whenever a method is applied in a new research area, it is advisable to review its underlying assumptions and evaluate if those still apply. Every research method and the underlying theories in which they are embedded are based upon a set of assumptions. Means-end chain analysis is a composition of several research techniques, like attribute elicitation and laddering interviews, which can be selected flexibly upon the researchers preference. This makes it challenging to find all the
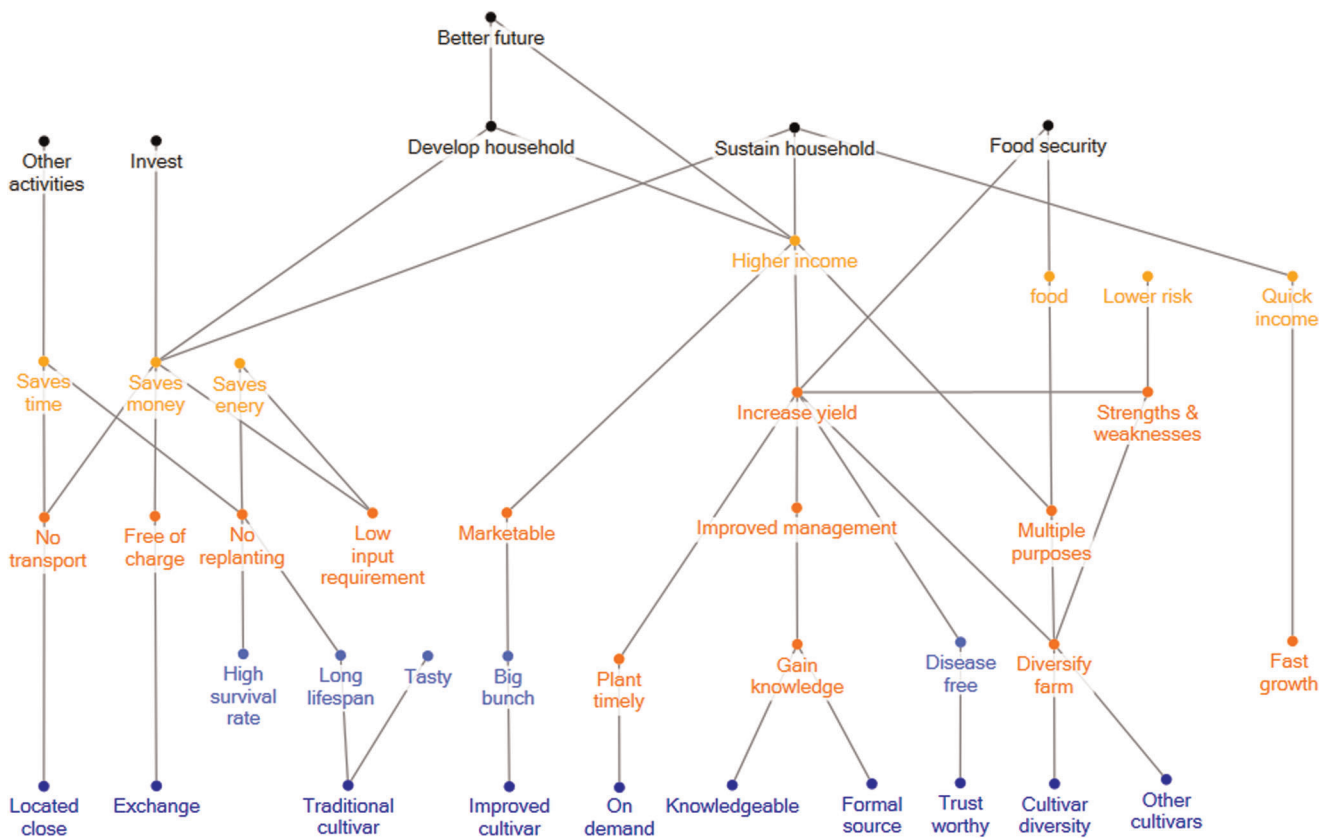

FIGURE 3 Number-of-respondents-based (*n*) hierarchical value map (n-HVM). Hierarchical value map based on the number of respondents (*n*) making a linkage between constructs. Attributes are presented in blue, consequences in orange and values in black. *n* = 31; cut-off level: *n* = 4 [Color figure can be viewed at wileyonlinelibrary.com]

assumptions that underly both method and theory as they are scattered in literature and are specific to each study.

An example of an assumption underlying means-end chain theory is that associations are hierarchical and causal: attributes lead to consequences, and consequences lead to values (ACV hierarchy). Reynolds and Olson (2001) argue that: "one can even ask whether causality as a central guiding principle for organizing experience may be culture-specific, that is, mostly applicable to the Western civilizations." The hierarchy assumption has been contested and was found to not hold in all cases (van Rekom & Wierenga, 2007). In our study, associations were not always made along the same hierarchy. "Expanding the farm" for example can be a value that is achieved by earning more money, but was for some farmers the means to generate more money or reach food security. However, it might be more appropriate to attribute this to the fact that farmers are producers than to culture-specific differences. In any type of production it is common to invest part of the profits made, to make more profits. While interviewing producers it can therefore be expected that profit is named circular with investments, expanding and purchase of more production goods, rather than linear.

Another assumption underlying means-end chain analysis is that consumers cope with the tremendous diversity of choice by grouping products to reduce complexity (Fransella et al., 2004). A difference to take into consideration is that farmers are not regular consumers when it comes to buying farm inputs. They are customers investing in their own means of production. In that sense, they are experts and might take more aspects into consideration and make a more thorough decision. When applying means-end chain analysis, farmers, in contrast to regular consumers, might come up with more attributes and more elaborated ladders.

In our study, the average number of attributes elicited was 7 and the average number of ladders 16. This resulted in a total of 88 constructs and 420 links. While browsing through means-end chain literature, the number of elicited attributes and ladders seems to be relatively high and the percentage of linkages shown in the HVM low. Reynolds and Gutman (1988) state that: "It is typical that a cut-off of 4 relations with 50 respondents and 125 ladders will account for as many as two-thirds of all relations among elements." A HVM with a cut-off level of 4, among 31 respondents, showing less than a quarter of the total linkages thus seems to be relatively low. However, differences in the number of elicited attributes, ladders, and linkages and the share of them being presented also depends on the elicitation technique, laddering method, coding and condensation, cut-off level, and so forth. In addition, not all studies report the number of constructs and links elicited nor the percentage of them presented in the HVM. This makes it hard to make any comparative claims to confirm if means-end chain analysis with "experts" as consumers indeed leads to more constructs and more elaborate ladders.

4 | CONCLUSION

The means-end chain analysis continues to be applied in a diverse field of scientific disciplines. Despite an extensive body of literature, there is no standardized or formalized way to apply the means-end

chain method, and many methodological variants exist. This paper has made new contributions to the methodological debate. It has not led to a more standardized method but rather to understanding the outcomes of different ways of application.

In this paper we have discussed four methodological issues that all seem to be related to underlying assumptions and the research area in which the mean-end chain method is applied. One of those assumptions is that people evaluate products and services based on dichotomous distinctions. There might be multiple underlying reasons why a person or a group of people do/do not perceive a certain dichotomy. This is a relevant consideration when means-end chain analysis is applied to compare groups of consumers. A second consideration is whether and how those dichotomous elicited constructs should be coded. We argue there is a difference between "coding" responses given in own words into common denominators and "condensing" responses by grouping subordinate constructs into a superordinate denominator. Condensing responses results in an increase and a loss of information at the same time. For studies aiming to understand *how* products or services are evaluated for example to improve product development, lower levels of condensation are more relevant, as more detailed information on the attributes is displayed. Studies focussed on marketing and advertisement or understanding *why* products are valued, might benefit of higher levels of condensation as it increases the probability attributes are linked to higher end constructs. A third unclarity addressed in this paper is which responses should be aggregated in the implication matrix. Frequency-of-responses-based aggregation favors individually dominant linkages relative to commonly shared linkages whereas number-of-respondents-based aggregation favors commonly shared linkages. Moreover is it not always clear what algorithm is used by available software to analyze laddering data. We therefore recommend researchers to explore how the used software program transform their ladders into chains presented in hierarchical value maps. Lastly, when means-end chain analysis is applied in a new research area it is relevant to evaluate the underlying assumptions. It is for example plausible that professional consumers come up with more personally relevant constructs and more elaborated ladders than regular consumers.

In conclusion, it does not seem possible to decide on "a best way" to apply means-end chain analysis. Different kinds of elicitation techniques, coding approaches, and aggregation algorithms can provide relevant information. The flexibility and differences rather allow for its application to understand a broad range of research questions. What is important is that researchers are aware of the effects of different ways of application, use this knowledge to make informed decisions in their research design, and report which decisions they have made and why.

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