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Deriving heterogeneous experts weights from incomplete linguistic preference relations based on uninorm consistency

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ABSTRACT

In this study, we provide an expertise-based weight allocation approach for heterogeneous experts with incomplete linguistic preference relations (ILPRs) in heterogeneous group decision-making (HGDM). Based on the uninorm consistency (U-consistency) theory, this paper proposes a new four-way iteration step to estimate the missing preference values so as to preserve the original information as much as possible. After obtaining the complete linguistic preference relations that satisfies reciprocity and boundedness, the discrimination indicator is introduced to measure the expertise level of heterogeneous experts, and its definition and calculation method in linguistic context is provided. In contrast to complete preference information, when assigning weights for heterogeneous experts with ILPRs, the contradictory relationship between their inconsistency and incompleteness, which had been proved by numerical simulation, exists and needs solving. Then, using defined discrimination, inconsistency and incompleteness, we propose a New-Index and a weight allocation method, the validity of which had been illustrated by the numerical example, to measure objectively heterogeneous experts' expertise. Considering these three indicators, the proposed weight is more reasonable than existent weight allocation methods with single indicator.

1. Introduction

Heterogeneous group decision-making (HGDM) is a process participated by several experts with heterogeneous information (referred to as heterogeneous experts) to jointly prioritize from alternatives. Conforming to complex varying realistic decision-making situations, it has not only gained an increasing attention from scholars [5,14,22,45,66] in recent years but also been successfully applied to selection of ERP system [23] and green supplier, as well as order allocation [26]. Coming from various professional fields, heterogeneous experts' unique characteristics in knowledge, background, skills, personality and experience may have different impact on the final result of HGDM [34,65]. Heterogeneous experts need to be given different weights to reflect their influence or importance in solving problems. However, there is certain risk in weight allocation process which might affect directly experts' participation enthusiasm in decision-making [34]. Therefore, objective allocation of expert weights is one of the issues most worth studying in HGDM [7,65,68].

With advantages like flexible, user-friendly, direct, and close to reality, especially in expressing certain qualitative characteristics of the said decision problem such as air quality, phone appearance, car comfortableness, project's R&D risks [5,18,33,48,58], linguistic preference relations (LPRs) in pairwise comparison provides an effective tool for heterogeneous experts to evaluate alternatives in decision-making. With ever perfecting and maturing technologies of natural language processing and artificial intelligence, LPR will have further development and application in reality [11]. However, experts may not give all necessary preference information in actual decision-making resulting in incomplete linguistic preference relations (ILPRs), due to time pressure, lack of knowledge or data, limited expertise in distinguish better alternative from the rest [6,11,31,36,48,57,60]. Hence the focus of this paper is on weight distribution of heterogeneous experts with ILPRs.

Different from complete information, challenges for expert weights allocation in ILPRs are: first, how to complement for certain expert's ILPR to obtain heterogeneous expert weights in incomplete information situation? Then how to solve the problem of contradiction between incompleteness and the inconsistency? On

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the one hand, the higher the incompleteness of ILPR (the more the number of missing values), the less the effective information the expert can provide, hence the lower his judgment and the smaller his weight should be given. On the other hand, the consistency of the higher incompleteness ILPR after its completion is also higher. High consistency is often regarded as high expert's judgment, i.e., the lower the inconsistency, the higher the weight. Therefore, this paper starts from the following two steps to solve the problem:

(1) Completion of heterogeneous experts' ILPRs. According to the existing literature, missing values of ILPR are estimated mainly by using known values and consistency. However, existing researches have the following drawbacks coping with this problem: estimates of missing elements through ILPR completion methods may be beyond the given range of LPRs or do not meet the reciprocity property as in [60]. Other methods may have information loss during the completion process of incomplete preference, as in [28,29]. Obviously, unreasonable values and information distortion caused by completion of the ILPR are bound to result in certain deviation in subsequent calculation of experts' expertise. So, it is necessary to improve the existing methods of estimating missing elements.
(2) Measurement of heterogeneous experts' expertise. HGDM has the advantage of making full use of experts' heterogeneous information, including different background, knowledge and skills, as well as problem solving experiences, etc. The heterogeneity is mainly reflected in experts' expertise [15]. Therefore, how to accurately identify and measure expertise is critical in giving weights to heterogeneous experts. The expertise of an expert is defined as the skill of distinguishing similar but not identical situations and of repeating his/her judgment coherently, i.e., the ability to differentiate consistently in assessing alternatives [46,51]. However, existing methods of measuring experts' expertise consider only consistency or consistency & discrimination. Simple consideration of consistency & discrimination is not enough in measuring experts' expertise, due to the conflict between inconsistency and incompleteness in ILPR. At this point, it is very challenging to balance among consistency, incompleteness, and discrimination. Therefore, it is necessary to put forward a new method to measure expertise in ILPR.

Inspired by the above challenges, this paper aims to research into expert weights allocation based on uninorm consistency (U-consistency) in HGDM and ILPR. The U-consistency was proposed recently on the basis of the representable uninorm operator. It is at present the most generic and most reasonable measurement of preference relation consistency [3,4,13,48]. Using the U-consistency, the weight allocation of heterogeneous experts with ILPRs is mainly addressed by two ways: (1) This paper proposed a four-way iterative method to estimate the missing elements in ILPR, so as to get complete LPR that satisfies the reciprocity and boundedness simultaneously. (2) Measurement of discrimination and inconsistency through calculating each preference value's repetitions in the completed LPR, whereby constructed a New-Index to measure heterogeneous experts' expertise, and to obtain their weights.

Main contributions of this study might be as follows: (1) Four kinds of linguistic U-consistency expressions were provided, using the complementary characteristics of LPRs and uninorm transitivity. Then, a four-way uninorm-based procedure was proposed for completing ILPRs, combined with a pre-completion process and an iterative process. The preference relations after completion using this new method satisfied completely the reciprocity and boundedness conditions. Improving existing ILPR iterative completion methods could be a contribution to the ILPR theories. (2) Definition of expert's discrimination indicator in ILPR context, i.e., the average deviation between repetitions of all linguistic preference values and the indifference value, and proved its rationality. In addition, numerical simulation verified the negative correlation between inconsistency and incompleteness in ILPRs, whereas most previous studies focused on descriptive illustrations. This provided theoretical basis for introducing the three indicators, namely, discrimination, inconsistency and incompleteness, into measuring expert expertise in ILPR. (3) Construction of a New-Index, using discrimination, inconsistency and incompleteness, to measure expert expertise, and proposed an expertise induced ordered weighted average (E-IOWA) operator. On this basis, an expert weight allocation method based on expertise was put forward. For HGDM and ILPRs, this method can get not only the order of expert importance but also expert weight vector.

The rest of the paper is organized as follows. Section 2 reviews the related literature while Section 3 introduces the necessary concepts and definitions. In Section 4, we propose four ways of linguistic U-consistency and put forward a revised iterative estimation procedure for completing ILPRs. After that, Section 5 proposes the weight allocation method of heterogeneous experts by defining a New-Index to measure their expertise level. Section 6 presents a numerical example to illustrate the proposed method. Section 7 makes comparison and discussion to verify the validity of the proposed method. Finally, Section 8 concludes the whole study.

2. Literature review

The research of HGDM is the supplement and extension of group decision-making (GDM) theory, so it is necessary to expound the context of GDM theory. GDM refers to the process of forming a judgment or a solution for a decision problem based on the input and feedback of several experts, and it has been widely applied to fields of economic management, medical treatment, new product design, weather forecast, risk assessment, etc. [41]. In earlier GDM research, all experts' preference information was considered equally important, i.e. assuming all experts are homogeneous [45]. In-depth development of GDM theories recognized that experts may have different influence on the final decision owing to their backgrounds, interests, knowledge or abilities [34,65]. In practice, some complicated GDM problems often involve several cross-domain heterogeneous experts. Therefore, HGDM has become the trend in the field of GDM in recent years [34,45,65,67]. HGDM research, meanwhile, will provide the theoretical basis for the effective application of group decision support systems (GDSS), due to the fact that the group decision model and algorithm constitutes the core of GDSS [43]. With the rapid development of information technology and knowledge-based systems, GDSS is integrated into the Web or mobile environment, which greatly facilitate the user's decision-making in practice. For example, Ma et al. [41] proposed a fuzzy multi-criteria GDSS called Decider, which can effectively deal with the fuzzy information of GDM under multi-level criteria. Subsequently, Lu et al. [39] presented a theme-based comprehensive evaluation model using the fuzzy hierarchical criteria GDSS for new products development. More recently, Morente-Molinera et al. [43] proposed a GDSS using the mobile technology and fuzzy ontology for mobile terminals. However, this paper focuses on HGDM theory and method, which could also be used to build GDSS to aid experts in reaching a final decision.

Since individual preference processing and preference aggregating are the keys to solve the HGDM problem [40], hence the following is a brief review of completion of ILPRs and allocation of expert weights which are related to this study.