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RESEARCH ARTICLE

Identifying Learning Leaders in Online Social Networks Based on Community of Practice Theoretical Framework and Information Entropy

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ABSTRACT The dynamic shifts in educational settings have led scholars to explore online social networks (OSNs) as emergent environment for learning communities. Recognized for their effectiveness in fostering lifelong learning, these online groups surpass traditional educational methods in scope and impact. However, they require meticulous management to maintain efficacy and facilitate knowledge sharing. Addressing this need, the current study introduces the objective of identifying and defining learning leaders to aid in the management of these learning communities. To achieve this, two innovative metrics have been developed, rooted in the theoretical framework of Community of Practice (CoP) and the principles of information entropy: the Learning Leader Metric (LLM) and the Weighted Learning Leader Metric (WLLM). The LLM evaluates three key areas: Learning Engagement, Expertise, and Domain Relevance, forming a comprehensive tripartite framework. In contrast, the WLLM enhances this evaluation by applying information entropy to assign varying weights to these dimensions, thus refining the assessment process while preserving computational efficiency. These metrics operate in an unsupervised manner, addressing the challenge of the absence of annotated data which is a common hurdle in supervised learning scenarios, particularly in information retrieval tasks. Tested against five established expert finding models, the empirical results of this study confirm that both LLM and WLLM demonstrate superior effectiveness in accurately identifying highly relevant experts compared to other models considered in the analysis.

INDEX TERMS Expert finding, learning leaders, Twitter, community of practice, learning, social media.

I. INTRODUCTION

In this modern era, online knowledge sharing is pivotal in enhancing work performance, productivity, creativity, and social awareness. Consequently, knowledge dissemination is essential for the advancement of society, organizational efficiency, and overall quality of life [1], [2]. Knowledge sharing encompasses the distribution of knowledge through interactions among individuals or within communities [3], [4], [5].

Knowledge sharing is employed across various fields including neuroscience, computer and information science, climate science, biology and genomics, and physics. Notably, online knowledge sharing transcends specific areas or organizations, extending over a vast geographic expanse where individuals disseminate knowledge, even with strangers [6]. Web 2.0 technologies have facilitated this process, enabling individuals to share knowledge through posting content, receiving feedback, and utilizing social media platforms. These platforms include social networks, sharing economy networks, media sharing networks, consumer review networks, discussion forums, bookmarking and content curation networks, interest-based networks, blogging and publishing networks, and even anonymous social networks [1], [7].

Online Social Networks (OSNs) play a pivotal role in facilitating knowledge sharing activities. OSNs are platforms that enhance communication among users by offering specific features such as profile creation, messaging, posting,

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responding to posts, and storytelling [8]. Recently, OSNs have been utilized for the dissemination of both tacit [9] and explicit knowledge within online communities [10]. Research on knowledge sharing via OSNs spans multiple domains. For instance, studies have examined tourist knowledge-sharing behaviors on Facebook and TripAdvisor [11], focusing on senior tourists [12], and exploring the general intentions of tourists to share knowledge [13]. Additionally, Yahoo Answers' social network has been intensively analyzed regarding its capacity for knowledge sharing [14]. Furthermore, OSNs have been investigated for their potential in educational knowledge sharing, such as identifying factors that facilitate knowledge sharing on Facebook [15]. OSNs also significantly contribute to public health education and physician communication. They serve as platforms for publishing health information, hosting educational events, supporting local resources with information, obtaining feedback from colleagues, and facilitating consultations among physicians [16], [17].

The concept of online learning communities is elucidated within Wenger's Community of Practice (CoP) theoretical framework, which details its core components and the elements vital for a successful online CoP [18], [19]. One key element for maintaining an active online CoP is robust community building efforts [19]. Wenger suggests that the success of a CoP is linked to the presence of active members who propel the community forward. These individuals may serve as CoP coordinators or administrators, responsible for governing the CoP, managing its repository, evaluating its achievements, assessing the value it offers, and monitoring its progress. Electronic platforms support the efforts of these active members by providing administrative tools such as statistical reports, progress indicators, and reminders.

Nevertheless, the operational dynamics of these active members differ within OSNs, and identifying such individuals is crucial for the activation of online CoPs. Empirical research further supports the notion that active members are essential for navigating challenges inherent to the community's structure. For instance, rotating leaders from the central hub to the peripheral areas of the CoP has been shown to significantly foster the growth of the online community [20]. Additionally, active participation by members within the CoP not only enhances its vibrancy but also makes it more attractive to potential new members [20], [21], [22]. In this study, we will characterize these active participants as Learning Leaders through both a theoretical and technical lens. The identification and support of learning leaders bring several benefits, outlined as follows:

1) The capacity to engage with their digital presence, given that their accounts are recognized as online CoPs in accordance with the findings of Komorowski et. al [23]
2) The ease of obtaining answers to questions related to a particular field of interest.
3) The inclination to drive engagement within learning communities, which includes user accounts, Twitter lists, or hashtags [22], [24], [25], [26].
4) The potential to strategically involve learning leaders in cold-start online CoPs–such as those denoted by a new hashtag–to stimulate community interaction.

Hence, the present study aims to introduce the following contributions to the scholarly field:

1) **Introduction of learning leaders in OSN:** This study represents the first scholarly effort for defining the concept of learning leaders within OSN. By identifying individuals who exhibit leadership qualities in facilitating learning and knowledge sharing, the research sheds light on the role of these leaders in fostering collaborative learning within OSNs.
2) **Application of CoP Theoretical Framework Components in Developing a Learning Leader Metric (LLM) for Assessing Learning Leaders:** The research incorporates elements of CoP framework to develop LLM. By including aspects such as mutual engagement, the LLM offers a robust framework that merges content lexical attributes and network structural characteristics. This holistic approach is applied in unsupervised settings, enabling the effective and efficient assessment of learning leaders within OSNs.
3) **Utilization of information entropy in the development of a Weighted version of Learning Leader Metric (WLLM):** The study further enhances the LLM by incorporating the concept of information entropy. By assigning weights to different components of LLM on the level of uncertainty or information contained within each component, the weighted version of LLM allows for a more nuanced and accurate assessment of learning leaders' contributions.

The subsequent sections of this article are organized as follows: Section II provides a review of the relevant literature, detailing existing research in the domains of knowledge sharing and expert identification. Section III introduces our proposed methodology, offering an in-depth explanation of the techniques and strategies employed in this study. The experimental setup is detailed in Section IV, which includes a thorough description of the procedures and the dataset utilized for implementation. In Section V, we undertake a rigorous analysis of the results obtained, addressing the research questions and discussing the insights and understandings gleaned from the study. Finally, Section VI offers our concluding observations, summarizing the principal findings and proposing directions for future inquiry and investigation.

II. LITERATURE REVIEW

Within this section, we provide a comprehensive background of knowledge, as discussed in section II-A, alongside an exploration of CoP theoretical framework in section II-B, which serves as an interpretive framework for understanding knowledge sharing within online learning communities. Subsequently, in section II-C, we offer a comprehensive overview of studies that have prominently employed data mining and machine learning techniques while utilizing the theoretical components of CoP. Furthermore, section II-D delves into the examination of studies pertaining to expert finding systems within OSNs. In section II-E, we provide a brief background about information entropy, a concept widely used in data mining and information theory. By organizing these discussions, we aim to provide a comprehensive understanding of the existing literature surrounding knowledge sharing and CoP theory, as well as the application of data mining techniques, expert finding systems within OSNs, and the concept of information entropy.

A. KNOWLEDGE: DEFINITIONS, TYPES, AND SHARING

To rigorously explore the mechanics of knowledge, it is imperative to conceptualize knowledge itself. Knowledge is an intricate construct that can be elucidated by distinguishing between data and information, which are foundational to knowledge. Data consists of raw, uninterpreted facts devoid of intrinsic meaning or value, serving as the groundwork for information. Information emerges from data through processes such as contextualization, categorization, calculation, correction, and condensation [27]. Consequently, information is processed data endowed with meaning, capable of influencing the judgment of its recipient. Moreover, the transformation of information into knowledge occurs through mechanisms like comparison, consequences, connections, and conversation [27]. Nonaka [28] further delineates the distinction between information and knowledge, asserting that "information is a flow of messages, while knowledge is created and organized by the very flow of information, anchored on the commitment and beliefs of its holder." Knowledge is perceived through various dichotomies, such as tacit versus explicit, focal versus tacit, and hard versus soft knowledge. Notably, knowledge can manifest both hard and soft characteristics concurrently. Hard knowledge is explicit, clearly articulate, and tangible. In contrast, soft knowledge is tacit, elusive, and indirect, often embodied in experiences that are challenging to articulate. Soft knowledge can be categorized into two types: socially constructed knowledge, which arises from social interactions, and internalized domain knowledge, which Winograd and Flores [29] describe as "lost in the unfathomable depths of obviousness." While much scholarly attention has been paid to hard knowledge, soft knowledge has been relatively overlooked. However, Wenger [30] posits that explicit knowledge represents only a fraction of the entire knowledge spectrum and that significant learning occurs through community engagement. Thus, there is a pressing need for further studies to delve into the nuances of soft knowledge.

The basic knowledge sharing model incorporates several key elements: source and recipient, object to share, process of sharing, and sharing environment. Knowledge can originate from personal or impersonal sources and must be accessible at individual or organizational levels, with trust and motivation playing critical roles in facilitating this access. The knowledge shared can be tacit, requiring personal interaction for transfer due to its non-codable nature, or explicit, easily shared through formal communication methods like databases. The sharing process itself is structured into four stages: initiation to identify knowledge gaps, implementation to exchange resources, ramp-up for the recipient's use of knowledge, and integration to assimilate this knowledge into routines. Lastly, the environment in which knowledge is shared affects the efficacy of the process, with different setups favoring the sharing of tacit or explicit knowledge; for example, equity-based alliances are more suitable for tacit knowledge, while contract-based alliances better support explicit knowledge sharing [2], [31], [32].

Knowledge creation and sharing are main resource for a CoP. Many organizations determined to establish or raise CoP instead of constructing teams due to its strong role in knowledge creation and sharing [33]. Lave and Wenger [34] draw the first line in raising the awareness of tacit and explicit knowledge creation, continuation, and sharing in their book about suited learning. The next section describes CoP concept and its main features.

B. COP THEORETICAL FRAMEWORK

The notion of CoP was first introduced by Lave and Wenger [34] in their book of situated learning. The concept has been subject to various interpretations by scholars and researchers. It is described as "groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis" [35]. In general, CoP is a place that join people (newcomers with experts, or so-called old-timers) to develop their skills in a specific domain of knowledge. learning happens when newcomers engage in activities with experts and gain expertise by continues engagement. "legitimate peripheral learning" indicate the evolvement from a newcomer to an old-timer, and "situated learning" means the underlying learning model.

As noted by Wenger-Trayner [36], the characteristics of CoPs include joint enterprise, mutual engagement, and shared repertoire. However, Cuddy et al. [35] refined these characteristics, renaming them as domain, community, and practice, which serve as fundamental elements in defining CoPs. The domain is "the area of knowledge that unites the community, confers its identity, and delineates the critical issues that members must address" [35]. The community is defined as a collective of individuals who engage and build interpersonal relationships around issues pertinent to a specific domain. Whereas, practice is the "set of shared repertoires of resources that include experiences, stories, tools, and ways of addressing recurring problems."

Wenger [18] identifies thirteen elements crucial for the success of online CoPs, enhanced by technology. These elements include presence and visibility, ensuring community visibility through directories and availability indicators;

rhythm, maintained via regular events and activities supported by online tools; and diverse interactions, facilitated by various technological platforms allowing synchronous and asynchronous communication. Efficient participation is essential, integrated seamlessly into daily routines and enhanced by flexible, technology-supported time management. Both short-term and long-term values are critical; technology aids in delivering immediate benefits through FAQs and expert access, while also supporting long-term value through content organization and retrieval systems. External connections are fostered through digital news and expert directories, while personal and communal identities are shaped through profiles, rankings, and public access to community missions. Belonging and relationships are strengthened by features like private chats and mentoring options. Technology also helps manage complex boundaries within the community by providing different access rights and spaces. Evolution of the community is supported by flexible digital platforms that adapt to its growth and changing needs. Lastly, active community-building is facilitated by administrative tools that help leaders manage and evaluate the community's progress and impact.

In addition, engagement holds pivotal significance within the context of CoP due to two fundamental rationales: Firstly, engagement is crucial for identity construction, a core element in social learning theory as articulated by Wenger-Trayner [36]. Wenger posits that participation in a CoP not only facilitates the acquisition of new knowledge but also aids in the formation of personal identity. He asserts, "Because learning transforms who we are and what we can do, it is an experience of identity. It is not just an accumulation of skills and information, but a process of becoming–to become a certain person or, conversely, to avoid becoming a certain person" [30]. Thus, identity construction is a manifestation of learning, and to construct identity, there are three modes of identification: engagement, imagination, and alignment. Imagination involves constructing an image of the practice and envisioning oneself as a member of the community. Alignment, on the other hand, entails adhering to the community's directives and expectations to achieve communal goals.

Secondly, engagement fosters what Wenger describes as horizontal accountability among members, contrasting with vertical accountability. Wenger emphasizes the strength of horizontal accountability generated through mutual commitment in a learning partnership within a CoP: "Participation in a community of practice can give rise to very strong horizontal accountability among members through a mutual commitment to a learning partnership. Even a good conversation creates accountability, albeit of a temporal and tacit nature" [36]. This form of accountability differs from vertical accountability, which is associated with traditional hierarchies, decision-making authority, management of resources, bureaucracies, policies, and regulations, as well as audits and inspections. Both forms of accountability, vertical and horizontal, are essential to promote effective learning within a CoP.

C. THE APPLICATION OF COP FRAMEWORK IN TECHNICAL STUDIES

Research employing data mining and machine learning techniques within online CoPs is segmented into several pivotal phases: construction, development, and monitoring. Each phase employs specialized machine learning techniques to optimize community functionality and user engagement. Khousa et al. [37], [38] utilized clustering algorithms such as seeded k-means and pairwise-constraints k-means to develop online communities aimed at enhancing career development opportunities for students. Efforts were made to promote the development of online CoPs by predicting forthcoming topics and questions for co-learners and mentors [39], [40]. Additionally, the expansion of online CoPs was scrutinized by examining factors that bolster community development and member increment through methods like Social Network Analysis (SNA), and the analysis of content, context, sentiment, and emotional aspects of discourse [20], [21]. Furthermore, SNA was employed for detecting online CoPs and monitoring their status in conjunction with statistical and content analysis via the Navivo [23], [41].

However, these investigations have not fully integrated core CoP concepts into their technical framework interpretations. For example, the metrics proposed in [21], applied to discussion forums, primarily relied on parameters such as the number of replies, topics, message length, and the duration of discussions. These metrics inadequately captured essential engagement components within the CoP framework, such as participation and reification. Moreover, to the best of our knowledge, none of the existing studies have introduced mechanisms for recommending experts to facilitate the development of online CoPs by integrating content aspects with indicators of expertise and engagement in a manner that is both efficient and effective. Consequently, this study aims to define and recommend such learning leaders, who embody a distinct category of experts. These leaders will be elaborated upon further in Section III-A.

D. EXPERT FINDING IN SOCIAL MEDIA

A diverse array of techniques for expert identification has been developed, ranging from traditional approaches to advanced neural network models. A significant body of research focusing on the discovery of experts has emerged within the realm of Community Question Answering (CQA), particularly since 2019, as documented in the literature [42]. Within these CQA platforms, innovative neural network methodologies have been deployed, including the use of transformers for encoding the features of experts and the application of pre-training strategies to fine-tune natural language processing models like BERT. The proliferation of studies within these communities may be linked to the availability of labeled datasets or the presence of a ground

TABLE 1. Comparative summary of expert finding models and techniques on Twitter.

Model	Structural Features	Textual Features	Method
Twitter-Rank [43]	follow relation	tweets	PageRank, LDA
Cognos [44]	number of twitter list	List titles and descriptions	Node centrality, TF-IDF
SSGR+RM [45]	follow, member and subscriber relation , similarity relation in graph structure	Bios, meta lists, tweets	TF-IDF, normalized Laplacian regularization
SeTRL [46]	topics similarity relation.	Tweets sentiment.	Expert classifier sentiment-weighted and topic relation-regularizer
FAME [47]	"Add-list-member" relation in weighted directed graph	list title, and description	Personalized PageRank, Word2Vec
AuFIN [48]	number of twitter list, followers, and following	use's bio and list title and description	BM25, semantic reranking (BERT), query expansion
CombMNZ [49]	mention relation	user documents	Voting model and the Correlation between document search and expert search

truth dataset, where expertise is ascertained through the assessment of answer quality, or within scholarly networks like, which facilitates the development and validation of new models.

Conversely, there has been a more limited application of expert finding studies in OSN such as Twitter. Table 1 provides a summary of the features and techniques utilized for expert detection on Twitter, outlining the various approaches adopted in the identification process.

As outlined in Table 1, a diverse array of techniques has been utilized for expert identification in unsupervised settings. Notably, AuFIN [48] distinctively employed a Bidirectional Encoder Representations from Transformers (BERT) for the semantic reranking of experts on Twitter. This innovative approach by AuFIN [48] is largely due to the introduction of the first labeled dataset for expert identification on Twitter in the Arabic language. Previous efforts in Expert Finding on Twitter often avoided manual annotation due to its labor-intensive, costly, time-consuming nature, and susceptibility to subjective biases. The 'Who To Follow' (WTF) service by Twitter, which has since been discontinued, was previously used to compile lists of top experts for various topics, supplemented by manual evaluations of the results [47], [50]. With the discontinuation of the WTF service, this method of expert labeling is no longer feasible. Furthermore, the datasets utilized in SeTR [46], Cognos [44], and SSGR+RM [45] are not publicly accessible. As a result, the only publicly available dataset for evaluating the proposed models currently is AuFIN [48], highlighting the limited availability of resources in this research area.

In addition to technical hurdles, assessing an individual's expertise level within professional or academic contexts remains a significant challenge [51], particularly in OSNs. Experts are not merely users with an interest in a specific subject area. Previous research has often lacked a robust theoretical framework for defining online experts. The datasets used in AuFIN [48] were specifically crafted to identify authorities, a distinct category of experts, as they articulate that "not all experts are authorities." Consequently, these studies have not established a theoretical foundation for defining experts and have primarily relied on practical experiments to identify experts within specific domains.

E. INFORMATION ENTROPY

The theory of information provides a mathematical framework to understand the dynamics of information transmission, processing, and storage [52]. At the core of this theory lies the concept of information entropy, which quantifies the amount of information inherent in the possible outcomes of a variable. High entropy indicates greater uncertainty and unpredictability in the outcome, reflecting a more diverse set of information. The entropy $H(X)$ of a discrete random variable X, with possible values $x_1, x_2, \ldots, x_n$ and a probability mass function $P(x)$, is defined as [53]:

$$H(X) = -\sum_{i=1}^{n} P(x_i)\, log\, P(x_i) \tag{1}$$

Here, $P(x_i)$ represents the probability of X taking the value x_i. This foundational concept in information theory is not only crucial for theoretical pursuits but also has practical applications in diverse fields including communications, network science, image processing, and both machine learning and artificial intelligence

In machine learning, entropy is employed as a metric for assessing the impurity or randomness within datasets. It plays a significant role in decision tree algorithms, aiding in the selection of the optimal attribute for node splitting [54]. Additionally, entropy has been utilized to refine methods for identifying influential nodes in complex networks [55]. It allows a proposed method to adaptively balance the influence of each attribute, based on the characteristics of the underlying network data.

In this study, we leverage entropy to calculate the information gain provided by each component of LLM, enhancing our understanding of its contributory elements to overall performance.

III. METHODOLOGY

In this section, we delineate the concept of learning leaders, drawing upon social learning theory and the foundational elements of CoP theoretical framework (section III-A). Subsequently, we will develop LLM based on our interpretation of the CoP framework and insights derived from previous research in section III-B. Finally, we describe the application

TABLE 2. Key differences between Influencers, Experts, and Learning Leaders.

	Influencers	Experts	Learning Leaders
Engagement	✓	x	✓
Specialists	x	✓	✓
Formal Language	x	✓	✓

of information entropy to the components of the LLM to establish the Weighted version of LLM in section III-C.

A. THE DEFINITION OF LEARNING LEADERS IN ONLINE COPS

The formulation of learning leaders is a composite derived from the concepts of leadership and the active mechanisms within learning communities. Leadership is recognized as a fundamental pillar within the online CoP framework, which also encompasses domain, community, and practice as its core elements [56]. Wenger pointed out that the effectiveness of online CoPs heavily relies on having a diverse and distributed leadership structure within the community [19]. Interestingly, Wenger noted that these leaders are not always the most knowledgeable experts. While experts contribute significantly to the educational dynamics of learning communities, their role does not necessarily equate to sustaining the community [19].

Leaders are distinguished by their strong social influence that motivates others to work together towards common goals. In the realm of online learning communities, leaders are individuals who motivate and involve their peers in scholarly discussions and activities, thus advancing the group's educational aspirations [57]. Leadership within virtual communities is often perceived as an evolutionary phase in the life-cycle of a member. The role of a leader is exemplified by an individual who not only actively contributes to the community but also possesses extensive personal networks and steers the direction of ideas and educational initiatives [58]. In the realm of online learning communities, Wenger identified various leadership modalities critical to the sustenance of these communities, including coordination, networking, and expertise, as well as learning leadership specifically. He distinguished expert leaders as those who possess and disseminate specialized knowledge, while learning leaders are regarded as members who curate and synthesize knowledge and lessons learned [19].

Technically, online learning leaders are considered as both experts and influencers. Experts are users with expertise in specific topics where influencers are users with strong connections with others. However, there is a confusion between the concept of influencers and influence maximization. In [59], they pointed out that influence maximization is very different from finding influential individuals, due to the following reasons:

- Influential nodes are based on relation's strength whereas influence maximization based on low-degree relations that help in disseminating information.
- The best influential nodes are not necessarily an influence maximization since the influence spread of them maybe overlapped.
- They are used for different application. For example, influence maximization is not used for cold-start recommendation scenario, where appropriate users are recommended to newcomers.

Hence, learning leaders are influencers based on their engagement with others. The differences between influencers, experts, and learning leaders are summarized in Table 2.

As illustrated in Table 2, influencers, experts, and learning leaders are each defined by distinct characteristics:

- Influencers engage with a wide audience but are not necessarily specialists in a specific field.
- Experts possess specialized knowledge but may not actively engage or influence others within the community.
- Learning leaders combine the expertise of specialists with active engagement, often using formal language to communicate their knowledge.

The distinctions can be summarized as follows:

- Influencers exert their influence through active engagement, which may be grounded in general knowledge rather than specialized expertise.
- Learning leaders also influence through engagement, but their influence is bolstered by their specialized knowledge within a specific domain.
- Experts are recognized for their specialization and may use formal language, yet they do not necessarily engage with others to the extent influencers or learning leaders do.
- The language employed by learning leaders tends to be more formal, reflecting their specialized knowledge, while influencers often use a more informal tone.

In essence, the objective of expert finding is to identify the most knowledgeable individuals within a specific topic [42]. whereas influencer finding focuses on identifying the most engaged users. Learning leaders are described as individuals who engage in the collective social process of learning, thereby encouraging other participants to immerse themselves in learning by means of active participation, intellectual engagement, and emotional commitment [57]. Broadly construed, learning leaders are recognized for their dynamic engagement and their propensity to foster similar engagement among others, leveraging their knowledge in a specific field and social influence within the learning community.

B. LLM CONSTRUCTION

As mentioned previously, learning leaders are distinguished by their dual role as both specialists in their respective domains and highly engaged users.

To accurately evaluate these individuals, LLM must incorporate a tripartite measurement framework, capturing the dimensions of engagement, expertise, and domain relevance. The engagement exhibited by learning leaders is of a particular nature, distinct from general forms of user interaction. Drawing upon Wenger's CoP theoretical framework [34] this study advances the concept of Learning Engagement as a novel construct. This form of engagement is characterized by its alignment with the principles of CoP, emphasizing not just interaction but the pursuit of shared learning outcomes within the community.

1) MEASUREMENT OF LEARNING ENGAGEMENT

Scholarly literature has introduced novel metrics designed based on theories to evaluate user behavior within online social networks such as Twitter and Facebook. Bonsón and Ratkai employed theoretical constructs from dialogic, stakeholder, and legitimacy theory to create new metrics that assess user engagement and social legitimacy within these digital platforms [60]. Their proposed metrics encompass popularity, which is akin to the 'like' feature; commitment, analogous to the 'comment' feature; virality, related to the 'share' feature; and social legitimacy, which is assessed via content analysis. Furthermore, Mariani et al. adopted a tripartite typology of engagement metrics to assess user engagement: generic engagement, brand engagement, and user engagement [61]. These metrics utilize interactions such as likes, comments, and shares as indicative measures. However, it is acknowledged that, to date, no extant research has specifically focused on engagement within learning communities with the utilization of CoP theoretical framework [19].

Engagement within learning communities is distinct from other forms of engagement due to its potential to facilitate meaningful learning, which is contingent upon the dual processes of participation and reification [30]. Participation refers to the interactive dynamics among community members, while reification involves the creation of artifacts (such as text documents, images, and other tangible outputs) within the process of negotiation.

In the context of online learning communities, engagement is manifested through activities, conversation, reflections, and other personal contributions, as well as the production of both physical and conceptual artifacts, encompassing tools, concepts, methodologies, narratives, documents, links to resources, and other tangible embodiments of the collective experience. These artifacts serve as focal points around which community participation is organized [62]. In essence, reification is the process of objectifying experience, thereby transforming fluid interactions into tangible entities.

The two facets of learning engagement are intrinsically interrelated; reification absent of participation yields mere artifacts devoid of intrinsic meaning, while participation without reification results in interactions that are ephemeral, unstructured, and lacking coherence [36].Thus, both processes are imperative for fostering a robust and meaningful engagement in learning environments.

Furthermore, the delineation of online interactions into categories of participation and reification presents a complex challenge that "cannot be answered unambiguously" [63]. Wenger has expounded upon this complexity, noting that the articulation of human meaning through language constitutes a form of reification, while simultaneously, the negotiation of meaning via dialogue, which employs language, forms pure participation [30]. Essentially, the negotiation of meaning encompasses both the reification and participation dimensions. Nevertheless, online interactions exhibit a pronounced tendency towards reification due to the inherent properties of digital communication, such as the automatic archiving of exchanges and the capacity to track and review past interactions. Stommel has posited that interactions within online forums should still be considered as participation, given that participants retain the ability to alter the content within these interactions, thereby engaging with the reified elements [63]. Wenger et al. have also acknowledged that technological advancements have introduced novel modalities of participation and reification within community interactions [62]. These technologies enable diverse and innovative forms of interaction and connectivity among individuals, fostering communal participation. Moreover, they provide enhanced mechanisms for the creation, storage, sharing, and management of artifacts, thereby expanding the scope and nature of reification in digital spaces.

Consequently, a more understanding is needed for the classification of online learners' behaviors into categories of participation and reification within OSNs like Twitter. The dichotomy of participation and reification is not straightforward, as these processes often coexist, manifesting in various forms and to varying extents [30], [64]. By referencing the definitions of participation and reification previously articulated, we might consider 'Retweets' and 'Likes' as instances of reification, whereas 'Comments' and 'Quotes' could be identified as forms of participation. Wenger and White have recognized the use of 'Mention' feature on Twitter, which directs a post to a specific individual, as a form of participation [62]. They also noted that comments within a document contribute a conversational dimension to the artifact, thereby qualifying as participation. On Twitter, the comments are organized into a sequential structure, defined as a "conversation structure where individual contributions to the dialogue are aggregated in a coherent, ordered manner" [65]. Thus, each comment or reply is part of a sequence of conversational turns known as the Turn Construction Unit (TCU). In the realm of conversation analysis, each constituent element of a conversational turn is termed a TCU, which is integral to the assessment of participation. For the purposes of this study, we will consider the comments on tweets and all associated TCUs as the primary indicators for measuring participation, given their prominence as representatives of the negotiation of meaning process.

Building upon the premise that Twitter's functionalities facilitating reification should support the processes of creation, storage, and dissemination of artifacts, Wenger and White have situated these tools along a continuum that spans participation and reification [62]. This placement is contingent on the tools' capacity to enable participation and reification processes. Consequently, they deduced that the functionalities which allow for the generation, archiving, and sharing of artifacts are aligned with reification. Conversely, functionalities that catalyze conversation and group activities are aligned with participation. Accordingly, features such as retweets, bookmarks, and media attachments are considered to support reification processes. Conversely, the 'Like' feature on Twitter may serve multiple purposes: it can be used to archive a tweet for later reference, as an expression of appreciation similar to a succinct conversational nod, or as a signal to garner attention and potentially initiate a dialogue. However, returning to the essence of participation, which involves active discussion and co-construction of meaning with the goal of facilitating learning, the 'Like' feature does not inherently contribute to this discourse. While it indicates a level of engagement, it lacks the depth required for true participatory learning. Therefore, it cannot be categorized as participation. This superficial interaction does not facilitate the deep, reflective, or collaborative exchanges that characterize meaningful learning interactions. However, it does indicate reification since it serves as a tangible record of user interaction, marking the content as noteworthy or valuable in some respect. This act of marking can be seen as creating a digital artifact within the social media landscape, contributing to the collective knowledge construction by signaling content worth noting or revisiting. It is imperative that each post be assessed for elements of participation and reification independently to accurately reflect the degree of learning engagement.

The selection of the features–comments, quotes, likes, and retweets–is predicated on their public visibility and higher reliability as compared to other features, such as bookmarks, which are private. Anchored in the preceding hypotheses, the functionality offered by Twitter, and the synthesis of extant literature, the following learning engagement metric is proposed:

$$PA(u) = No.Comments + No.Quotes \tag{2}$$

$$RE(u) = No.Retweets + No.Likes \tag{3}$$

$$LE(u) = \log_2 [(\frac{\sum_{n=1}^{P} \text{PA (u)} + \text{RE (u)}}{2}) + 2] \tag{4}$$

In the proposed framework, let *PA* denote participation, *RE* represent reification, *LE* stand for learning engagement, and P correspond to the total number of posts by user u. We considered that some users may lack other's engagement with their posts on Twitter, hence we added 2 when computing the logarithm for smoothing in case of both *PA* and *RE* are zero.

2) EXPERTISE MEASUREMENT

The metrics for finding expertise are designed to identify subject matter experts regardless of their specific knowledge domains. A variety of Twitter features have been tested to assess a user's level of expertise. Research on expert finding models [44], [47], [66] within Twitter has demonstrated that the relationship between users and lists (user-list relation) is a potent indicator of a user's expertise. Furthermore, the study employing the SSGR+RM approach [45] revealed that a leverage of user data–including the user's biography, tweets, and metadata from Twitter lists–with structural information obtained from a graph-based normalized Laplacian regularization framework is superior. This framework utilizes various relational data points, such as follow-user, member-of-list, follow-list, and list-list relationships, and has shown more effectiveness than the Cognos system [44]. Additional studies [50], [67] have identified a trend where experts typically amass a larger following than standard social media users. Moreover, network features, such as the number of followers and friends a user has on Twitter or the global comments score on Reddit, exhibit a robust capacity to differentiate experts from non-experts [68]. Additionally, the SETRL framework [46] has yielded two key insights: firstly, the sentiment of tweets–whether strongly negative or positive–can signal a user's depth of understanding regarding the topics they discuss. Secondly, semantic relationships between topics inferred from topic co-occurrence in a user's knowledge base, which is extracted from their biography, have been found to surpass the effectiveness of lexical relations between topics as delineated in WordNet. This is especially the case concerning the relatedness and relevance of expertise topics.

The Authority FINding in Arabic Twitter (AuFIN) framework [48] incorporates a strategy for identifying experts, underpinned by two foundational assumptions: experts tend to have a larger follower base, and experts are typically included in numerous Twitter lists [48]. The computational model for this identification is illustrated in Equation(5).

$$E\ (u) = log2(L(u) + 2)(\frac{F(u)}{A(u)} + 2)] \tag{5}$$

wherein F, A, and L denote the user's total number of followers, friends, and memberships in Twitter lists, respectively. Similar to the equation of *LE*, the scoring metric accounts for the possibility that an expert might not be listed in any Twitter lists by implementing an additive smoothing technique, where a constant of 2 is added to both factors. This adjustment ensures that the score is smoothed in instances where the list membership count is zero. This particular metric has been selected for utilization in this study.

3) MEASUREMENT OF DOMAIN RELEVANCE

Investigations into the utility of lexical features from users' tweets on Twitter have revealed that these features are minimally indicative of expertise [69]. In contrast, the lexical characteristics embedded in users' biographical sections and the descriptions of their lists emerge as the most salient indicators of expertise [48]. In our proposed metric, we utilize a straightforward and efficient approach for measuring specialty by employing lexical matching between a user's document u (which includes biography and Twitter list descriptions) and the query corresponding to the community description c . This approach is favored due to its simplicity and computational efficiency. For this purpose, the BM25 algorithm [70] with predefined default parameters– $k1 = 0.9$ and $b = 0.4$ –is utilized, which operates on the basis of the following equation:

$$DR(u, c) = \frac{IDF * ((k1 + 1) * tf)}{(k1 * ((1 - b) + b * (dl / avgdl)) + tf + epsilon)} \tag{6}$$

where *tf* denotes Term Frequency within a specific document, *IDF* indicates the Inverse Document Frequency of a term across the entire corpus of documents, *dl* is the Document Length, *avgdl* represent the Average Document Length across the document set, *k1* is a tuning parameter that normalizes term frequency, *b* form a parameter for normalizing document length, and *epsilon* is a negligible constant introduced to the denominator to obviate division by zero contingencies [71].

Upon the previous determination of appropriate metrics for learning engagement, expertise, and domain relevance, the cumulative model for ascertaining the paramount learning leaders among users with respect to a community description is devised through the summation of these individual metrics, delineated as follows:

$$LLM(u, c) = LE(u) + E(u) + DR(u, c) \tag{7}$$

The integration of the tripartite framework–Learning Engagement, Expertise, and Domain Relevance–ensures that a candidate for a learning leader role is evaluated comprehensively. Consider a scenario where a candidate is assessed solely based on expertise, with this proposed expertise measured through the concept of crowd wisdom [72]. Crowd wisdom, as demonstrated in carefully constructed lists by Twitter users, can be a potent indicator of topical expertise. Furthermore, research by Ishfaq et al. [73] has shown that the "wisdom of Twitter crowds" can serve as supervised information for identifying topical experts. While metrics such as the number of list membership, followers, and following can indicate a candidate's expertise, they do not reveal the candidate's specific domain of expertise. This is where the Domain Relevance metric becomes crucial, bridging the gap between the candidate and the community description. However, assessing a candidate's expertise and domain relevance alone does not reflect their ability to share knowledge or lead effectively. These capabilities are gauged through the Learning Engagement metric, which ensures that the candidate is evaluated across these three critical areas, forming a well-rounded view of their potential as a learning leader on platforms like Twitter. Having an expert in a relevant domain does not necessarily make them a learning leader if they lack leadership skills and the ability to share knowledge. Similarly, a candidate who is engaged and relevant to a domain of knowledge does not automatically qualify as a real expert, especially if their expertise has not been validated by the collective wisdom of the crowd. Moreover, an expert leader whose domain of relevance does not align with the online CoP's focus will likely not bring significant benefits to the community. Therefore, the effectiveness of a learning leader on Twitter or similar platforms depends on a balanced assessment of their engagement, expertise, and relevance to the domain. Only through this comprehensive evaluation we can ensure the selection of a candidate who is not only knowledgeable but also capable of leading and enriching the learning environment within their community.

C. WLLM CONSTRUCTION

In a manner akin to the Multiple Local Attributes-weighted Centrality (LWC) [55] model and Evidence Theory Centrality (ETC) [74], where entropy weighting is utilized to synthesize multiple local centrality measures, thereby enhancing the model's discriminative performance and accuracy, we advocate for the introduction of an entropy weighting mechanism. This mechanism is designed to calculate the individual weight of each metric within a composite framework, with the objective of more effectively identifying learning leaders. The overall ranking of a learning leader is subsequently calculated using an entropy-weighted sum of the three component metrics. The implementation of entropy weighting facilitates the discrimination between users while ensuring a manageable computational complexity, quantified as *O(n)*. A succinct delineation of this proposed method is outlined subsequently:

1) A matrix is constructed where columns correspond to the values of three distinct measurements, and each row corresponds to an individual user within a social network comprised of n users, denoted by the set $U = u_1, u_2, \ldots, u_n$, the decision scheme can be expressed as $D = \{d_1, d_2, \ldots d_n\}$. We will use the metrics described earlier, LE, E, and DR as the evaluation indices that can be expressed as $A = \{a_1, a_2, a_3\} = LE, E, DR$. Then, $d_i(a_j)$ ($i = 1, 2, \ldots, n; j = 1, 2, 3$) represents the j_{th} index of user i. The final matrix P can be obtained as follows:

$$P = \begin{bmatrix} d_1(a_1) & d_1(a_2) & d_1(a_3) \\ d_2(a_1) & d_2(a_2) & d_2(a_3) \\ \cdots & \cdots & \cdots \\ d_n(a_1) & d_n(a_2) & d_n(a_3) \end{bmatrix} \tag{8}$$

2) Normalization of the matrix is executed through dividing each element within the matrix by the maximal value present in its corresponding column, which is formalized as:

$$r_{ij} = \frac{d_i\ (a_j)}{\max\{d_i\ (a_j)\}} \tag{9}$$

This normalization ensures that the matrix is suitably scaled and proportioned for subsequent analytical processes.

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & r_{n3} \end{bmatrix} \tag{10}$$

3) Calculate information entropy of each evaluation index as follows:

$$E_j = -\ln(n)^{-1}\sum_{i=1}^{n} r_{ij}\ln r_{ij} \ \ (j = 1, 2, 3)] \tag{11}$$

4) Calculate the weight for each evaluation index as follows:

$$w_j = \frac{E_j}{\sum_1^3 (E_j)} \tag{12}$$

5) The computation of WLLM for each user is accomplished through the application of a weighted summation. The value WLLM for a given user u_i is determined by the following expression:

$$WLLM(u_i) = \sum_{j=1}^{3} w_j \, r_{ij} \tag{13}$$

The algorithmic time complexity of the WLLM is subjected to a meticulous analysis. The initial step involves the computation of three specific measurements: *LE, E*, and *DR* for a cohort of *n* users. Each of these measurements incurs a computational complexity of *O(n)*. During the second step, the normalization process has a complexity of *O(n)*. Subsequently, in the third and fourth steps, the entropy weighting method is employed to assign appropriate weights to the three evaluative indices, which collectively exhibit a computational complexity of *O(3n)*. The fifth step entails the calculation of a weighted sum to ascertain the WLLM value, which possesses a complexity of *O(n)*. Consequently, the total algorithmic time complexity for the WLLM algorithm is the summation of these individual complexities, which is: $O(n) + O(n) + O(3n) + O(n)$ Upon simplification, this equates to an overall complexity of *O(n)*, aligning with the time complexity reported for LWC [55]. In this study, we employed a re-ranking metric that does not consume time as much as the first stage of information retrieval. This approach was necessitated by the lack of comprehensive data needed to execute the ranking process for all users. We managed to collect 300,000 posts for the purpose of implementing re-ranking, which served as a means to assess the performance of our metric in comparison to other metrics applied to re-rank the same list of candidates.

IV. EXPERIMENTAL SETUP

To evaluate the efficacy of LLM and its weighted counterpart WLLM, we orchestrated a comparative analysis against two established ranking methodologies–BM25 and expertise reranking [48], as well as three state of the art models in the domain of expert finding models. These modern frameworks encompass a profile-centric model (Cognos), a graph-oriented model (FAME), and a document-driven approach (CombMNZ). A brief description of each model is delineated below:

- BM25 [70]: This method is equivalent to the utilization of *DR* score exclusively, which serves as a component of the LLM.
- Expertise reranking [48]: This approach employs the product of the *DR* score and *E* score, both of which are integral to the LLM.
- Cognos [44]: This model leverages the product of the quantity of Twitter lists a user appears on and the lexical similarity between the query and the user's profile, as measured using Term Frequency-Inverse Document Frequency (TF-IDF).
- FAME [47]: This technique utilizes Twitter lists and the PageRank algorithm to identify influential users within an edge-labeled graph. In this graph, users are represented as nodes, and the 'add-list-member' relationship–between the list creator and the list members–is depicted. This relationship is annotated with the list's name and description. The graph undergoes pruning to remove nodes with the lowest in-degree and out-degree.
- CombMNZ [49]: This method adopts a document-based voting model for expert identification. The search process adheres to the framework outlined in the TREC Enterprise track 2005 [75], which encompasses various levels of lexical matching and co-occurrence matching. Initially, relevant user documents are retrieved; thereafter, each user is scored based on the relevance scores of their retrieved documents.

The results of state-of-the-art models used in our comparative analysis are derived from the reference [48]. The experimental dataset utilized in this research is the Authority Finding in Arabic Twitter (AuFIN) corpus, also referenced from [48]. This corpus is the only publicly available collection designed for expert finding within the context of OSN. The dataset includes a collection of tweets segmented into three domain sectors: health, sports, and politics. These tweets act as queries that are assumed to outline the description of a learning community. During the relevance evaluation phase, experts were assessed and divided into two clear categories: relevant and highly relevant. The experimental design aims to rerank the top 100 users retrieved by the BM25 algorithm, utilizing both the LLM and WLLM for enhanced ranking precision.

Worth mentioning that the dataset queries were partitioned into five subsets, or folds. The present experiment utilized the fifth fold only to facilitate the computation of *LE*, as we complemented the dataset by crawling twitter to have the data required to compute *LE*. The selected fold encompassed 10 queries from each of the three categorical domains, amounting to a total of 30 queries. A substantial corpus of 300,000 Twitter posts was accumulated, where for each user

TABLE 3. A detailed description of the test set.

Query Categories	No. of Queries	No. of Users per Query	No. of Posts per User	No. of Relevant Experts	No. of Highly Relevant Experts
Health	10	100	100	30	40
Sport	10	100	100	28	48
Politics	10	100	100	17	32

TABLE 4. Evaluation of proposed metrics (LLM and WLLM) against baseline retrieval systems. Bold numbers indicate the best performance per evaluation measure.

Model	P@1	P@5	P@10	NDCG@5	R@20	R@50
BM25	**0.267**	0.127	0.090	0.164	0.179	0.259
Expertise	0.233	0.133	0.103	0.200	0.233	0.328
LLM	**0.267**	0.127	0.113	0.203	0.251	**0.333**
WLLM	**0.267**	**0.140**	**0.117**	**0.212**	**0.256**	0.331

within the top 100 rankings of each query 100 posts were retrieved. It is important to note that retweeted content was excluded from the analysis on the grounds that it does not constitute original authorship by the user in question. The specific attributes of the test collection are systematically enumerated in Table 3, which delineates the dataset as encompassing 30 queries, 3,000 users, 300,000 posts, and 195 experts deemed relevant to the study.

To assess the efficacy of the LLM and WLLM, we employed established evaluation metrics commonly used in the assessment of retrieval systems [48], [76]. These metrics include Precision at ranks 1, 5 and 10 (P@1, P@5, and P@10), Normalized Discounted Cumulative Gain at rank 5 (NDCG@5), and Recall at ranks 20, 50, and 100 (R@20, R@50, and R@100). Precision at the specified ranks (P@1, P@5, and P@10) is indicative of the system's capability to retrieve experts at the apex of a ranked list with depths of 1,5 and 10, respectively. NDCG@5 evaluates the rank positioning of highly relevant experts within the top segment of the list. Recall at varying depths (R@20, R@50, and R@100) reflects the proportion of retrieved experts relative to the total number of existing experts for each query.

Precision metrics (P@1, P@5 and P@10) and NDCG@5 were utilized to measure the performance of all models, including BM25, expertise reranking, Cognos, FAME, and CombMNZ. However, for the evaluation of Recall at different depths (R@20 and R@50), the comparison was limited to the results obtainable from BM25 and expertise reranking, as the corresponding metrics for Cognos, FAME, and CombMNZ were not available.

V. RESULTS AND DISCUSSION

In this section, we present and discuss the findings of our experiments, which were designed to address the following research questions:

- **RQ1**: Will LLM and WLLM improve the performance of experts finding models? (section V-A)
- **RQ2:** Will WLLM improve the results of LLM? (section V-B)

TABLE 5. Performance comparison of proposed metrics (LLM and WLLM) with State-of-the-Art systems. Bold numbers indicate the best performance per evaluation measure.

Model	P@1	P@5	NDCG@5	R@100
Cognos	0.173	0.085	0.114	0.336
FAME	0.040	0.029	0.034	0.158
CombMNZ	0.053	0.031	0.036	0.056
LLM	**0.267**	0.127	0.203	**0.347**
WLLM	**0.267**	**0.140**	**0.212**	**0.347**

- **RQ3:** What are the practical implications of LLM and WLLM for practitioners and researchers? (section V-C)

A. ENHANCING EXPERT IDENTIFICATION WITH THE LLM AND WLLM

In the field of systems that find experts, how precise the searches are at different stages and the importance of the search results' rankings are key for measuring how well the system works. The comparative outcomes are detailed in Tables 4 and 5. While the LLM model shows comparable results to the BM25 model in terms of P@1 and P@5, it exhibited superior performance in P@10 and the highest R@20 and R@50 among all models evaluated. This enhancement underscores the model's capacity to retrieve a more relevant set of documents across an expanded spectrum of top results. Furthermore, the LLM model evidenced a marginal improvement in NDCG@5 relative to conventional expertise metrics, indicating more effective prioritization of the top five results, especially in the identification of highly relevant experts.

These outcomes suggest that the LLM and WLLM model possesses a robust capability to recognize and rank highly relevant experts more effectively than other metrics. This implies that incorporating additional components of learning engagement significantly aids in identifying experts of high relevance to the query. Moreover, our comparative analysis with state-of-the-art models indicates that the LLM model offers a unique advantage by incorporating additional evaluative metrics absent in traditional models. Both Cognos and FAME primarily utilize structural features. Cognos relies on the total number of lists a user belongs to and the lexical similarity between a query topic and the list description. Similarly, FAME employs structural features concerning the list creator and members, with scores derived using a personalized PageRank algorithm. Additionally, the CombMNZ model emphasizes a voting mechanism based on textual relevance of documents and their co-occurrence relations with users. In contrast, our metric surpasses these models by including components such as learning engagement and expertise, along with the weighting scheme for each component, thereby enhancing the overall effectiveness of the model.

B. COMPARATIVE ANALYSIS OF LLM AND WLLM IMPROVEMENTS

The advantage of WLLM over LLM is further highlighted by performance metrics such as P@5, P@10, and NDCG@5.

The NDCG metric is particularly insightful as it places higher value on highly relevant experts appearing earlier in the rankings. Both WLLM and LLM surpass the baseline models, which rely on lexical ranking and expertise reranking, demonstrating their superior ability to identify and prioritize the most relevant experts effectively.

Further analysis using recall at depths of 20 and 50 reveals that both LLM and WLLM are capable of retrieving a wider array of relevant experts. This suggests that these metrics are particularly effective in discerning experts who not only are relevant but also exhibit the characteristics essential for learning leaders within their respective domains.

WLLM has demonstrated significant progress in identifying highly relevant experts, affirming its effectiveness in pinpointing Learning Leaders and recognizing a broader spectrum of experts. The similar performance of WLLM and LLM at P@1 suggests that the top recommendation remains consistent between the two models. This consistency could be attributed to the top-ranked individual or entity having a distinctly higher relevance score that is less affected by the weighting adjustments introduced in WLLM. Essentially, the most learning leader tends to be clearly distinguishable, irrespective of the specific weighting of components.

The slight underperformance of WLLM in the R@50 measure, compared to LLM, can be primarily attributed to the model's weighting scheme, which heavily depends on the values of the features. These values are calculated based on information entropy, as explained in section III-C. A significant challenge arises with non-public accounts. Since engagement metrics from these accounts are not accessible, the calculation of weights in WLLM, which relies on the actual values of these engagement metrics, is directly impacted. This lack of data can distort the information entropy values, leading to inaccurately weighted components. This issue becomes particularly problematic in broader evaluations like R@50, where capturing a wide array of relevant recommendations is crucial. The absence of engagement data from non-public accounts means that WLLM might not fully assess all potential learning leaders, leading to its observed underperformance in broader recall measures. This underscores the critical impact of available data on the effectiveness of models that use weighted components based on feature distribution and unpredictability.

From a computational perspective, WLLM determines the optimal weighting with low computational complexity $O(n)$ that can be generalized without the reliance on heuristics or empirical inferences such as linear interpolation. This efficient approach underscores WLLM's innovative design, which automatically identifies the most effective weights for enhancing retrieval performance. Furthermore, we anticipate that both LLM and WLLM would exhibit improved performance if applied during the first stage of user retrieval. This expectation stems from the notable results obtained by integrating the expertise score with the BM25 score for the initial retrieval, as implemented by Haouari et al. [48]. Our speculation is grounded in our comparative analysis of re-ranking the top 100 users using the expertise score with BM25 against the performance of LLM and WLLM. Nonetheless, we were unable to apply LLM and WLLM in the first phase of user retrieval due to constraints in our dataset.

C. PRACTICAL IMPLICATIONS OF LLM AND WLLM FOR PRACTITIONERS AND RESEARCHERS

Our proposed metrics, LLM and WLLM bring a comprehensive suite of capabilities that greatly benefit practitioners. These metrics facilitate the nuanced evaluation of community leaders through multi-faceted assessments that include textual profile matching, influence, expertise, and engagement. Such thorough assessments enable a more nuanced understanding of leadership dynamics within communities. Additionally, LLM and WLLM provide crucial insights into the growth and development of members within online learning communities. These insights are instrumental in identifying key learning trajectories and educational outcomes, supporting the continuous development of community members. The models also play a key role in analyzing the growth rates of communities by examining the status of members. They provide valuable metrics that aid in understanding trends in community expansion and engagement, which are vital for effective community management. Furthermore, LLM and WLLM are essential in activating emerging or cold start online learning communities. By recommending potential learning leaders, these models help quickly establish functional and interactive communities. In addition, LLM and WLLM applicability extends to various domains, such as rumor verification on Twitter, where their efficiency is demonstrated through minimal computational demands and reliance on publicly available data. This versatility makes the models practical and accessible for a wide range of uses, enhancing their value to practitioners across different fields.

For researchers, the LLM and WLLM, along with the LLM components of participation, reification, and learning engagement, provide essential tools for conducting evolutionary-historical analyses of online CoPs on OSNs. These metrics are useful for validating whether existing online CoPs meet the theoretical benchmarks set by Wenger et al. [62] for a successful online CoP. Their framework identifies three critical elements that drive the success of online CoPs:

- **Rhythms**: This aspect refers to the cyclic patterns of connection and disconnection among members of an online CoP concerning both time and space.
- **Interaction**: This element involves the patterns of communication and collaboration among community members via the concept of participation and reification. A crucial polar for knowledge exchange and the development of communal practices.
- **Identities**: This focuses on how individual and groups are shaped and expressed within the community, important for developing a sense of belonging and commitment.

By utilizing the LLM and WLLM, researchers can examine these dimensions within various CoPs to check their alignment with the theoretical model of success. Furthermore, these tools enable researchers to forecast the future dynamics of online CoPs and compare the behaviors of different learning communities. This comparative analysis is made possible through the metrics provided by the LLM and WLLM, which quantify engagement, participation, reification, influence, and expertise within community interactions. Such research not only deepens our understanding of what makes an online CoP successful but also enriches the broader disciplines of knowledge management and educational development.

VI. CONCLUSION

In the current investigation, we delve into the emergent field of identifying learning leaders–individuals who act as catalysts within learning communities, manifesting through hashtag-centric discussions [24] or account-based collectives [23]. These figures are crucial in facilitating the exchange of knowledge and fostering the educational dynamics within these groups. Our research introduces and applies metrics designed to assess the leadership qualities and expertise of individuals, drawing upon the theoretical framework of CoP, previous studies, and the application of information entropy. Empirical results from our experiments substantiate the effectiveness of these metrics, showcasing their capability in accurately identifying highly relevant experts.

Future endeavors will aim to adapt and apply these metrics across other types of OSN platforms such as Reddit, LinkedIn, and Facebook. Additionally, it is acknowledged that the semantic depth of language often extends beyond simple lexical matching in the extraction of domain-specific knowledge, an aspect that will be explored in subsequent studies. This also includes examining the semantics inherent in network structures. Moreover, integrating advanced methodologies such as multi-modal data integration and distributed computing frameworks into our assessment strategies will facilitate the real-time processing and analysis of data, improving the scalability and robustness of our metrics [77]. By incorporating these cutting-edge technologies and approaches, we aim to significantly enhance the precision and applicability of our metrics in identifying and evaluating learning leaders across diverse digital platforms.

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REFERENCES

[1] Y. Charband and N. J. Navimipour, "Online knowledge sharing mechanisms: A systematic review of the state of the art literature and recommendations for future research," *Inf. Syst. Frontiers*, vol. 18, no. 6, pp. 1131–1151, Dec. 2016.

[2] B. Niedergassel, "Introduction," in *Knowledge Sharing in Research Collaborations: Understanding the Drivers and Barriers*. Wiesbaden, Germany: Gabler, 2011, pp. 1–7, doi: 10.1007/978-3-8349-6217-1_1.

[3] A. Majchrzak, S. Faraj, G. C. Kane, and B. Azad, "The contradictory influence of social media affordances on online communal knowledge sharing," *J. Comput.-Mediated Commun.*, vol. 19, no. 1, pp. 38–55, Oct. 2013.

[4] J.-N. Lee, "The impact of knowledge sharing, organizational capability and partnership quality on IS outsourcing success," *Inf. Manage.*, vol. 38, no. 5, pp. 323–335, Apr. 2001.

[5] C. Tong, W. I. W. Tak, and A. Wong, "The impact of knowledge sharing on the relationship between organizational culture and job satisfaction: The perception of information communication and technology (ICT) practitioners in Hong Kong," *Int. J. Hum. Resour. Stud.*, vol. 5, no. 1, p. 19, Jan. 2015.

[6] J. Park and J. L. Gabbard, "Factors that affect scientists' knowledge sharing behavior in health and life sciences research communities: Differences between explicit and implicit knowledge," *Comput. Hum. Behav.*, vol. 78, pp. 326–335, Jan. 2018.

[7] S. Chai, S. Das, and H. R. Rao, "Factors affecting bloggers' knowledge sharing: An investigation across gender," *J. Manage. Inf. Syst.*, vol. 28, no. 3, pp. 309–342, Dec. 2011.

[8] H.-M. Lai and T. T. Chen, "Knowledge sharing in interest online communities: A comparison of posters and lurkers," *Comput. Hum. Behav.*, vol. 35, pp. 295–306, Jun. 2014.

[9] H.-M. Zhu, S.-T. Zhang, and Z. Jin, "The effects of online social networks on tacit knowledge transmission," *Phys. A, Stat. Mech. Appl.*, vol. 441, pp. 192–198, Jan. 2016.

[10] F. University, C. Phang, A. Kankanhalli, and R. Sabherwal, "Usability and sociability in online communities: A comparative study of knowledge seeking and contribution," *J. Assoc. Inf. Syst.*, vol. 10, no. 10, pp. 721–747, Oct. 2009.

[11] S. Okazaki, L. Andreu, and S. Campo, "Knowledge sharing among tourists via social media: A comparison between Facebook and TripAdvisor," *Int. J. Tourism Res.*, vol. 19, no. 1, pp. 107–119, Jan. 2017.

[12] M. J. Kim, C.-K. Lee, and M. Bonn, "The effect of social capital and altruism on seniors' revisit intention to social network sites for tourism-related purposes," *Tourism Manage.*, vol. 53, pp. 96–107, Apr. 2016.

[13] A. Bilgihan, A. Barreda, F. Okumus, and K. Nusair, "Consumer perception of knowledge-sharing in travel-related online social networks," *Tourism Manage.*, vol. 52, pp. 287–296, Feb. 2016.

[14] H. Shen, Z. Li, J. Liu, and J. E. Grant, "Knowledge sharing in the online social network of Yahoo! Answers and its implications," *IEEE Trans. Comput.*, vol. 64, no. 6, pp. 1715–1728, Jun. 2015.

[15] S. Moghavvemi, M. Sharabati, T. Paramanathan, and N. M. Rahin, "The impact of perceived enjoyment, perceived reciprocal benefits and knowledge power on students' knowledge sharing through Facebook," *Int. J. Manage. Educ.*, vol. 15, no. 1, pp. 1–12, Mar. 2017.

[16] E. K. Choo, M. L. Ranney, T. M. Chan, N. S. Trueger, A. E. Walsh, K. Tegtmeyer, S. O. McNamara, R. Y. Choi, and C. L. Carroll, "Twitter as a tool for communication and knowledge exchange in academic medicine: A guide for skeptics and novices," *Med. Teacher*, vol. 37, no. 5, pp. 411–416, May 2015.

[17] A. K. Lofters, M. Slater, E. Nicholas, and F.-H. Leung, "Facebook as a tool for communication, collaboration, and informal knowledge exchange among members of a multisite family health team," *J. Multidisciplinary Healthcare*, p. 29, Jan. 2016.

[18] E. Wenger, "Supporting communities of practice: A survey of community-oriented technologies," Version 1.3, CA, USA, 2001. [Online]. Available: https://api.semanticscholar.org/CorpusID:150495409

[19] E. Wenger, "Communities of practice: The structure of knowledge stewarding," in *Knowledge Horizons*. Evanston, IL, USA: Routledge, 2000, pp. 205–224.

[20] G. Antonacci, A. F. Colladon, A. Stefanini, and P. Gloor, "It is rotating leaders who build the swarm: Social network determinants of growth for healthcare virtual communities of practice," *J. Knowl. Manage.*, vol. 21, no. 5, pp. 1218–1239, Sep. 2017, doi: 10.1108/jkm-11-2016-0504.

[21] K. Hafeez, P. Foroudi, B. Nguyen, S. Gupta, and F. Alghatas, "How do entrepreneurs learn and engage in an online community-of-practice? A case study approach," *Behav. Inf. Technol.*, vol. 37, no. 7, pp. 714–735, Jul. 2018, doi: 10.1080/0144929x.2018.1474255.

[22] M. J. Homewood, "Twitteryvision: Using Twitter live chat to build communities of practice as a legal learning tool," in *Teaching Legal Education in the Digital Age*. Evanston, IL, USA: Routledge, 2022, pp. 36–46.

[23] M. Komorowski, T. D. Huu, and N. Deligiannis, "Twitter data analysis for studying communities of practice in the media industry," *Telematics Informat.*, vol. 35, no. 1, pp. 195–212, Apr. 2018.

[24] S. Gilbert, "Learning in a Twitter-based community of practice: An exploration of knowledge exchange as a motivation for participation in #hcsmca," *Inf., Commun. Soc.*, vol. 19, no. 9, pp. 1214–1232, Sep. 2016.
[25] A. Keir, N. Bamat, B. Hennebry, B. King, R. Patel, C. Wright, A. Scrivens, O. ElKhateeb, S. Mitra, and D. Roland, "Building a community of practice through social media using the hashtag #neoEBM," *PLoS ONE*, vol. 16, no. 5, May 2021, Art. no. e0252472.
[26] W. W. Xu, I.-H. Chiu, Y. Chen, and T. Mukherjee, "Twitter hashtags for health: Applying network and content analyses to understand the health knowledge sharing in a Twitter-based community of practice," *Qual. Quantity*, vol. 49, no. 4, pp. 1361–1380, Jul. 2015.
[27] T. H. Davenport and L. Prusak, *Working Knowledge: How Organizations Manage What They Know*. Cambridge, MA, USA: Harvard Business Press, 1998.
[28] I. Nonaka, "A dynamic theory of organizational knowledge creation," *Org. Sci.*, vol. 5, no. 1, pp. 14–37, Feb. 1994, doi: 10.1287/orsc.5.1.14.
[29] T. Winograd and F. Flores, *Understanding Computers and Cognition: A New Foundation for Design*, vol. 335. Norwood, NJ, USA: Ablex, 1986.
[30] E. Wenger, *Communities of Practice: Learning, Meaning, and Identity*. Cambridge, U.K.: Cambridge Univ. Press, 1999.
[31] H. Berends, H. van der Bij, K. Debackere, and M. Weggeman, "Knowledge sharing mechanisms in industrial research," *R D Manag.*, vol. 36, no. 1, pp. 85–95, Jan. 2006.
[32] C. Chen, "The effects of knowledge attribute, alliance characteristics, and absorptive capacity on knowledge transfer performance," *R D Manag.*, vol. 34, no. 3, pp. 311–321, Jun. 2004.
[33] J. Nirenberg, "From team building to community building," *Nat. Productiv. Rev.*, vol. 14, no. 1, pp. 51–62, Dec. 1994.
[34] J. Lave and E. Wenger, *Situated Learning: Legitimate Peripheral Participation*. Cambridge, U.K.: Cambridge Univ. Press, 1991.
[35] C. Cuddy, "Cultivating communities of practice: A guide to managing knowledge," *Bottom Line*, vol. 15, no. 2, pp. 1–11, Jun. 2002.
[36] E. Wenger-Trayner, "Communities of practice and social learning systems: The career of a concept," in *Social Learning Systems and Communities of Practice*, C. Blackmore, Ed. London, U.K.: Springer, Jan. 2010, pp. 179–198, doi: 10.1007/978-1-84996-133-2_11.
[37] E. A. Khousa, Y. Atif, and M. M. Masud, "A social learning analytics approach to cognitive apprenticeship," *Smart Learn. Environ.*, vol. 2, no. 1, p. 14, Sep. 2015, doi: 10.1186/s40561-015-0021-z.
[38] E. A. Khousa and Y. Atif, "Social network analysis to influence career development," *J. Ambient Intell. Humanized Comput.*, vol. 9, no. 3, pp. 601–616, Jun. 2018, doi: 10.1007/s12652-017-0457-9.
[39] M. Rezaei, H. Bobarshad, and K. Badie, "Prediction of learner's appropriate online community of practice in question and answering website: Similarity in interaction, interest, prior knowledge," *Interact. Learn. Environments*, vol. 29, no. 4, pp. 670–687, May 2021.
[40] M. S. Rezaei, H. Bobarshad, and K. Badie, "Toward enhancing collaborative learning groups formation in Q&A website using tag-based next questions predictor," *Int. J. Technol. Enhanced Learn.*, vol. 11, no. 4, p. 441, 2019, doi: 10.1504/ijtel.2019.102570.
[41] J. Laru and S. Järvelä, "Social patterns in mobile technology mediated collaboration among members of the professional distance education community," *Educ. Media Int.*, vol. 45, no. 1, pp. 17–32, Mar. 2008, doi: 10.1080/09523980701847131.
[42] N. Nikzad-Khasmakhi, M. Balafar, and M. R. Feizi-Derakhshi, "The state-of-the-art in expert recommendation systems," *Eng. Appl. Artif. Intell.*, vol. 82, pp. 126–147, Jun. 2019.
[43] J. Weng, E.-P. Lim, J. Jiang, and Q. He, "TwitterRank: Finding topic-sensitive influential twitterers," in *Proc. 3rd ACM Int. Conf. Web Search Data Mining*. New York, NY, USA: Association for Computing Machinery, Feb. 2010, pp. 261–270, doi: 10.1145/1718487.1718520.
[44] S. Ghosh, N. Sharma, F. Benevenuto, N. Ganguly, and K. Gummadi, "Cognos: Crowdsourcing search for topic experts in microblogs," in *Proc. 35th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Aug. 2012, pp. 575–590.
[45] W. Wei, G. Cong, C. Miao, F. Zhu, and G. Li, "Learning to find topic experts in Twitter via different relations," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 7, pp. 1764–1778, Jul. 2016.
[46] Y. Xu, D. Zhou, and S. Lawless, "Inferring your expertise from Twitter: Integrating sentiment and topic relatedness," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell. (WI)*, Oct. 2016, pp. 121–128.
[47] P. Lahoti, G. De Francisci Morales, and A. Gionis, "Finding topical experts in Twitter via query-dependent personalized PageRank," in *Proc. IEEE/ACM Int. Conf. Adv. Social Netw. Anal. Mining*, Jul. 2017, pp. 155–162.
[48] F. Haouari, T. Elsayed, and W. Mansour, "Who can verify this? Finding authorities for rumor verification in Twitter," *Inf. Process. Manage.*, vol. 60, no. 4, Jul. 2023, Art. no. 103366.
[49] C. Macdonald and I. Ounis, "The influence of the document ranking in expert search," in *Proc. 18th ACM Conf. Inf. Knowl. Manage.* New York, NY, USA: Association for Computing Machinery, Nov. 2009, pp. 1983–1986, doi: 10.1145/1645953.1646282.
[50] G. Li, M. Dong, F. Yang, J. Zeng, J. Yuan, C. Jin, N. Q. V. Hung, P. T. Cong, and B. Zheng, "Misinformation-oriented expert finding in social networks," *World Wide Web*, vol. 23, no. 2, pp. 693–714, Mar. 2020.
[51] S. Lin, W. Hong, D. Wang, and T. Li, "A survey on expert finding techniques," *J. Intell. Inf. Syst.*, vol. 49, no. 2, pp. 255–279, Oct. 2017.
[52] C. E. Shannon, "A mathematical theory of communication," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 5, no. 1, pp. 3–55, Jan. 2001, doi: 10.1145/584091.584093.
[53] D. J. C. MacKay, *Information Theory, Inference & Learning Algorithms*. New York, NY, USA: Cambridge Univ. Press, 2002.
[54] M. Bansal, A. Goyal, and A. Choudhary, "A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning," *Decis. Anal. J.*, vol. 3, Jun. 2022, Art. no. 100071.
[55] J. Zhang, Q. Zhang, L. Wu, and J. Zhang, "Identifying influential nodes in complex networks based on multiple local attributes and information entropy," *Entropy*, vol. 24, no. 2, p. 293, Feb. 2022.
[56] O. Ceran and H. Bahadır, "Online communities of practice: Sustainable leadership model," *J. Learn. Teach. Digit. Age*, vol. 4, no. 1, pp. 25–33, 2019.
[57] M. K. Kim, Y. Wang, and T. Ketenci, "Who are online learning leaders? Piloting a leader identification method (LIM)," *Comput. Hum. Behav.*, vol. 105, Apr. 2020, Art. no. 106205.
[58] A. J. Kim, *Community Building on the Web: Secret Strategies for Successful Online Communities*, 1st ed., Reading, MA, USA: Addison-Wesley, 2000.
[59] Y. Yang, Z. Wang, J. Pei, and E. Chen, "Tracking influential individuals in dynamic networks," *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 11, pp. 2615–2628, Nov. 2017.
[60] E. Bonsón and M. Ratkai, "A set of metrics to assess stakeholder engagement and social legitimacy on a corporate Facebook page," *Online Inf. Rev.*, vol. 37, no. 5, pp. 787–803, Sep. 2013.
[61] M. M. Mariani, M. Mura, and M. Di Felice, "The determinants of Facebook social engagement for national tourism organizations' Facebook pages: A quantitative approach," *J. Destination Marketing Manage.*, vol. 8, pp. 312–325, Jun. 2018.
[62] E. Wenger, N. White, and J. D. Smith, *Digital Habitats: Stewarding Technology for Communities*. Portland, OR, USA: CPsquare, 2009.
[63] W. Stommel, "Conversation analysis and community of practice as approaches to studying online community," *Lang. Internet*, vol. 5, no. 5, 2008.
[64] P. M. Hildreth and C. Kimble, "The duality of knowledge," *Inf. Res.*, vol. 8, no. 1, pp. 1–20, 2002.
[65] A. Lantz-Andersson, "Facebook and conversation analysis: The structure and organization of comment threads," *CALICO J.*, vol. 36, no. 2, pp. 142–144, 2019. [Online]. Available: https://www.proquest.com/scholarly-journals/facebook-conversation-analysis-structure/docview/2271766743/se-2
[66] C. Wagner, V. Liao, P. Pirolli, L. Nelson, and M. Strohmaier, "It's not in their tweets: Modeling topical expertise of Twitter users," in *Proc. Int. Conf. Privacy, Secur., Risk Trust Int. Conf. Social Comput.*, Sep. 2012, pp. 91–100.
[67] C. Liang, Z. Liu, and M. Sun, "Expert finding for microblog misinformation identification," in *Proc. COLING*, 2012, pp. 703–712.
[68] B. D. Horne, D. Nevo, and S. Adalı, "Recognizing experts on social media: A heuristics-based approach," *ACM SIGMIS Database, DATABASE Adv. Inf. Syst.*, vol. 50, no. 3, pp. 66–84, Jul. 2019.
[69] Q. V. Liao, C. Wagner, P. Pirolli, and W.-T. Fu, "Understanding experts' and novices' expertise judgment of Twitter users," in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.* New York, NY, USA: Association for Computing Machinery, May 2012, pp. 2461–2464, doi: 10.1145/2207676.2208410.
[70] K. S. Jones, S. Walker, and S. E. Robertson, "A probabilistic model of information retrieval: Development and comparative experiments: Part 2," *Inf. Process. Manage.*, vol. 36, no. 6, pp. 809–840, 2000.
[71] A. Trotman, A. Puurula, and B. Burgess, "Improvements to BM25 and language models examined," in *Proc. Australas. Document Comput. Symp.*, Nov. 2014, pp. 58–65.

[72] K. Kaur and D. Bansal, "Techniques to extract topical experts in Twitter: A survey," in *Proc. Inf. Commun. Technol. Intell. Syst. (ICTIS)*, vol. 1. Singapore: Springer, 2018, pp. 391–399.

[73] U. Ishfaq, H. U. Khan, S. Iqbal, and M. Alghobiri, "Finding influential users in microblogs: State-of-the-art methods and open research challenges," *Behav. Inf. Technol.*, vol. 41, no. 10, pp. 2215–2258, Jul. 2022.

[74] J. Zhao, Y. Song, and Y. Deng, "A novel model to identify the influential nodes: Evidence theory centrality," *IEEE Access*, vol. 8, pp. 46773–46780, 2020.

[75] N. Craswell, A. P. De Vries, and I. Soboroff, "Overview of the TREC 2005 enterprise track," *TREC*, vol. 5, pp. 1–7, Nov. 2005.

[76] A. Yates, R. Nogueira, and J. Lin, "Pretrained transformers for text ranking: BERT and beyond," in *Proc. 14th ACM Int. Conf. Web Search Data Mining*. New York, NY, USA: Association for Computing Machinery, Mar. 2021, pp. 1154–1156, doi: 10.1145/3437963.3441667.

[77] J. Du, T. Lin, C. Jiang, Q. Yang, C. F. Bader, and Z. Han, "Distributed foundation models for multi-modal learning in 6G wireless networks," *IEEE Wireless Commun.*, vol. 31, no. 3, pp. 20–30, Jun. 2024.

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