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Modeling Academic Research Collaborator Selection Using an Integrated Model

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ABSTRACT Expert finding systems try to alleviate the information overload problem and recommend experts who can satisfy users' needs. They support researchers to find research collaborators automatically. The main challenge of current expert finding systems is that they retrieve experts based on the content of their documents but ignore the human interaction perspective. The human interaction perspective comprises the factors that influence collaborator selection decisions in real life. This study aimed to develop a collaborator selection model for expert finding systems in research universities. This model includes human capital, social capital, and cultural capital factors that influence collaborator selection. The researchers integrated the Scientific and Technical Human Capital (STHC) model and Social Capital Theory to determine these factors. The authors conducted a survey comprising 349 researchers from Malaysian research universities to validate the research hypotheses. A partial least squares structural equation model (PLS-SEM) was employed to analyze all the survey data. The empirical results revealed that the significant factors that influence collaborator selection in the research universities context were cognitive accessibility, reliability, relevance, commitment, physical accessibility, cultural experiences, complementary skills, and research experience. Surprisingly, the results revealed that network ties, relational accessibility, and reputation were insignificant factors for collaborator selection. This study proposed a research model for collaborator selection in the research universities context and provided several recommendations for the policymakers and practitioners. The model will help to provide sufficient criteria to select academic research collaborator in universities and can be used by expert finding systems designers, researchers, collaborators, and universities.

INDEX TERMS Expert finding systems, research collaboration, collaborator selection, scientific and technical human capital, social capital.

I. INTRODUCTION

Increasing knowledge production growth was characterized by a rise in scale and importance of scientific research collaboration [1]. Recently, the productivity of scientific research in universities has been one of the most significant concerns for economic policy [2]. Universities continually need to adjust their research approach to enhance scientific productivity and impact to achieve high-quality outcomes at the national and international levels. The research performance in universities is considered as an indicator for national and international ranking criteria [3]. Moreover, universities consider research collaboration as a technique to solve complicated and challenging problems and to improve competitive power [4]. Additionally, the rise of multidisciplinary and interdisciplinary research necessitates new

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research and collaboration mechanisms to conduct research effectively [5].

Effective research collaboration mainly depends on the skills and personality of the research collaborators [4]. Researchers may appear to collaborate, but the challenge concerns the individuals they collaborate with [6]–[9]. The increasing development of researchers' communities, a huge number of individuals, and the volume of available data on the web create significant obstacles for collaborator seekers to find a suitable research collaborator [10]. As defined by Katz and Martin [11], research collaborators are researchers who work together to advance scientific knowledge in research projects, scientific papers, or some other key aspects of scientific research. Selecting an effective research collaborator influences the efficiency of research collaboration [12]. Therefore, selecting a suitable research collaborator is a fundamental problem in research collaboration in universities, as it determines the success of collaboration [1], [6], [12]–[14].

Gathering information about collaborators and selecting them manually is a challenging process, especially in the case of large-scale and distributed organisations [15], [16]. Hence, Information Retrieval (IR) techniques can be used for finding experts using automated systems; these systems are called expert finding systems. They are IR systems that can recommend different experts and rank them according to their expertise on a particular topic. Their expertise can be extracted from expertise evidences such as the candidate's publications, reports, projects, social network, online and real-world activities of the candidates [17], [18].

Expert finding system helps organizations and individuals to search for suitable experts automatically [19]. Expert finding systems have been used widely to find research collaborators [12], [20]–[23].

According to a systematic review published by [21], the current research in expert finding systems focuses on developing a system based on suitable matches between the user query and content of the documents related to the experts. The problem with such systems is that they retrieve experts based on the content of the expert's documents and ignore the human interaction perspective [24]–[29]. Human interaction includes the factors that affect collaborator selection decisions in real-life [21], [24], [29]–[32]. For example, a collaborator may have a good record of publications. However, the individual may not communicate well, not be willing to collaborate, busy, or unwilling to share expertise with individuals who do not have positive affective relations. Hence, integrating the factors concerning human interaction with expert finding systems can improve their effectiveness [20], [22], [24], [32]–[36].

Furthermore, the current studies concerning expert finding systems retrieve collaborators based on the relevance between the user query and documents related to the collaborators and considered relevance as the most critical factor for collaborator selection [20], [23], [26], [35], [37]–[40]. However, there are limitations to this consideration. Firstly, the occurrence of a person several times with a topic does not always mean he/she is a real expert [26], [41]. Secondly, the repetition of an expertise topic in a document does not necessarily point to a solid association between the topic and the document [24]. In document retrieval, Xu and Chen [42] found that cognitive accessibility and reliability are also determinants of relevance. No previous study examined the effect of collaborators' reliability and cognitive accessibility on relevance.

Moreover, there are a limited number of studies on how collaborator seekers select research collaborators and the factors that influence their decision making [14], [43]–[46]. Bozeman *et al.* [44] studied the influence of career stage, gender, and work-style fit on collaborator selection. Corley and Sabharwal [46] found that collaborator name and country of residence are important characteristics for research collaborators. Moreover, Bozeman *et al.* [43] indicated that the collaborator's gender, age, national origin, and degree of study as personal factors and the field of training, and work experience as human capital factors are important for research collaborators. Furthermore, Gunawardena [45] found that job rank, research interest, and institution type specific to the research collaborators influence their selection.

Additionally, Stvilia *et al.* [14] examined the influence of resources, cost of tasks, culture, and collaborator personality on selection decision. As discussed above, previous researchers have examined three human capital factors. Along similar lines, Iglič *et al.* [1] stated that human capital is important for research collaboration. Thus, the influence of additional human capital factors for collaborator selection should be examined. Furthermore, research collaboration is about knowledge exchange, which is a social process that needs individual interactions [47]. Therefore, individual relationships are crucial for information exchange. Social capital is essential for successful collaboration [48]. The influence of social capital factors on collaborator selection was not studied in previous studies. In addition to human and social capital, cultural capital appears to have a critical role in collaborator selection [49], and it is often the most challenging barrier to overcome [4]. None of the previous studies examined the effect of cultural capital on collaborator selection. Therefore, expert finding systems designers need a human interaction-collaborator selection model that includes human capital, social capital, and cultural capital factors to be integrated with current expert finding systems in universities context. Thus, this study aims to address the following objectives: 1) to identify the human capital, social capital, and cultural capital factors that influence collaborator selection and how collaborator seekers prioritise these factors; 2) To examine the mediating role of relevance and physical accessibility on collaborator selection; 3) To develop a collaborator selection model for expert finding systems in research universities; 4) To provide recommendations for expert finding system designers to integrate the proposed collaborator selection model with current expert finding systems in the universities.

This study is structured in the following manner: Section 1 introduction about the study, Section 2 discusses the theoretical foundation and research hypotheses, Section 3 describes the research methodology, Section 4 and Section 5 describes and discusses the results, Section 6 provides recommendations for stakeholders, Section 7 presents the contributions of this study, Section 8 provides future work for upcoming researchers, Section 9 describes the limitations, and Section 10 presents the conclusion of the study.

II. THEORETICAL FOUNDATION AND RESEARCH HYPOTHESES

A. THEORETICAL FOUNDATIONS

This study developed a model by integrating the Scientific and Technical Human Capital (STHC) model with the Social Capital Theory (SCT) to explore human, social, and cultural capital factors that influence the researchers' decision to collaborate with a particular research collaborator. STHC is defined by (Bozeman, Dietz [50] as ''the pool of researcher's skills, technical knowledge, network ties, and resources widely defined'' (p.19). Additionally, Bozeman and Corley [51] and Iglič *et al.* [1] defined STHC as ''the distinctive collection of resources the researchers provide to his or her work and collaboration, such as research experience, knowledge, formal education, complementary skills, reputation, and network ties.'' (p.3) and (p.156-157). In addition to human and social capital, Corley *et al.* [49] found a need for cultural capital dimension for improving the STHC model Corley *et al.* [49] developed an extended STHC model that adopts the basic structure of the original model, which revealed that the professional capacity of scientists typically derives from human and social capital. However, the extended STHC model adds the cultural dimension along with human and social capital dimensions.

The three dimensions comprising the extended STHC model are human, social, and cultural capital. Human capital emphasizes on the individual endowment and formal training, which typically concerns professional training, education, personal health, and other factors [49]. There is no unique definition of human capital. Becker [52] refers to human capital as an individual's experiences, skills, and personal health. Manzari *et al.* [53] indicated commitment and reputation as being important human capital factors. Additionally, Iglič *et al.* [1] associated human capital with research experience, knowledge, formal education, complementary skills, and reputation. Thus, human capital represents the knowledge, experience, and skills gained from academic study, commitment, and reputation. Social capital concerns the relationships between individuals, which extend the scientist's social perspective and resources availability. Cultural capital considers cultural experiences that concentrate on interaction with individuals from diverse cultural backgrounds (such as gender, nationality, race, SES, and discipline).

The STHC model has been applied widely by several researchers [1], [51], [54]–[58]. Bozeman and Corley [51], Lee and Bozeman [54] studied how STHC affects scientific collaboration. Moreover, Lin and Bozeman [55] applied the STHC to identify the influence of previous industry experience of researchers on research outputs. The components of STHC can be used as independent constructs that may affect collaborations [49]. For instance, Jha and Welch [59] defined STHC factors (such as lab affiliation, joint appointment, grant average, and rank) to increase network ties. Moreover, Iglič *et al.* [1] applied STHC to investigate the influence of the human capital of researchers on scientific collaboration between different types of researchers.

In this research, the extended STHC model proposed by Corley *et al.* [49] has been selected to identify the factors that influence research collaborator selection decision. STHC was selected as the theoretical foundation because, according to the definition provided by Corley *et al.* [49], STHC is ''the sum of human, social, and cultural capital needed to participate in science.'' (p.12) Therefore, it can be used as a theoretical lens to identify the human, social, and cultural capital factors that research collaborators are expected to have in order to participate in research collaboration.

The Social Capital Theory (SCT) is defined by Nahapiet and Ghoshal [30] as ''the collection of the actual and probable resources available through, derived from, and embedded within the network of relationships owned by an individual or social unit.'' (p.243). Thus, social capital is a developing resource shaped by social relations between two or more members. Social capital improves the effectiveness of action, encourages collaboration, and affects innovative activity [60] Nahapiet and Ghoshal [30], Coleman [61] suggested that the associations among individuals are a potent source of action. Hence, SCT facilitates knowledge seeking by supporting the essential requirements for knowledge and information exchange. Nahapiet and Ghoshal [30] defined the three dimensions of SCT, namely, structural, cognitive, and relational. The structural dimension concerns the shape of the relations between the members of a network. It is about whom you communicate with and how. The cognitive dimension concerns the resources that provide shared topics of interests, languages, and explanations between the partners for successful collaboration. The relational dimension concerns comfort and trust in people and their information along with the willingness of the people to interact [60]. In this study, the theoretical model proposed by Woudstra *et al.* [62] was applied to examine the social capital factors that influence collaborator selection. This model considers the concept of social capital as a helpful framework in understanding interpersonal source selection and examining information exchange conditions which are information quality and access to information and information source.

According to the STHC model used for this research, human capital is about research experience, complementary skills, commitment, and reputation within the mind and personality of an individual. Human capital may not be sufficient for present-day research collaboration and complex innovation processes and often needs a multidisciplinary approach [63]. The social capital dimension of STHC is about network ties, which are important but not sufficient.

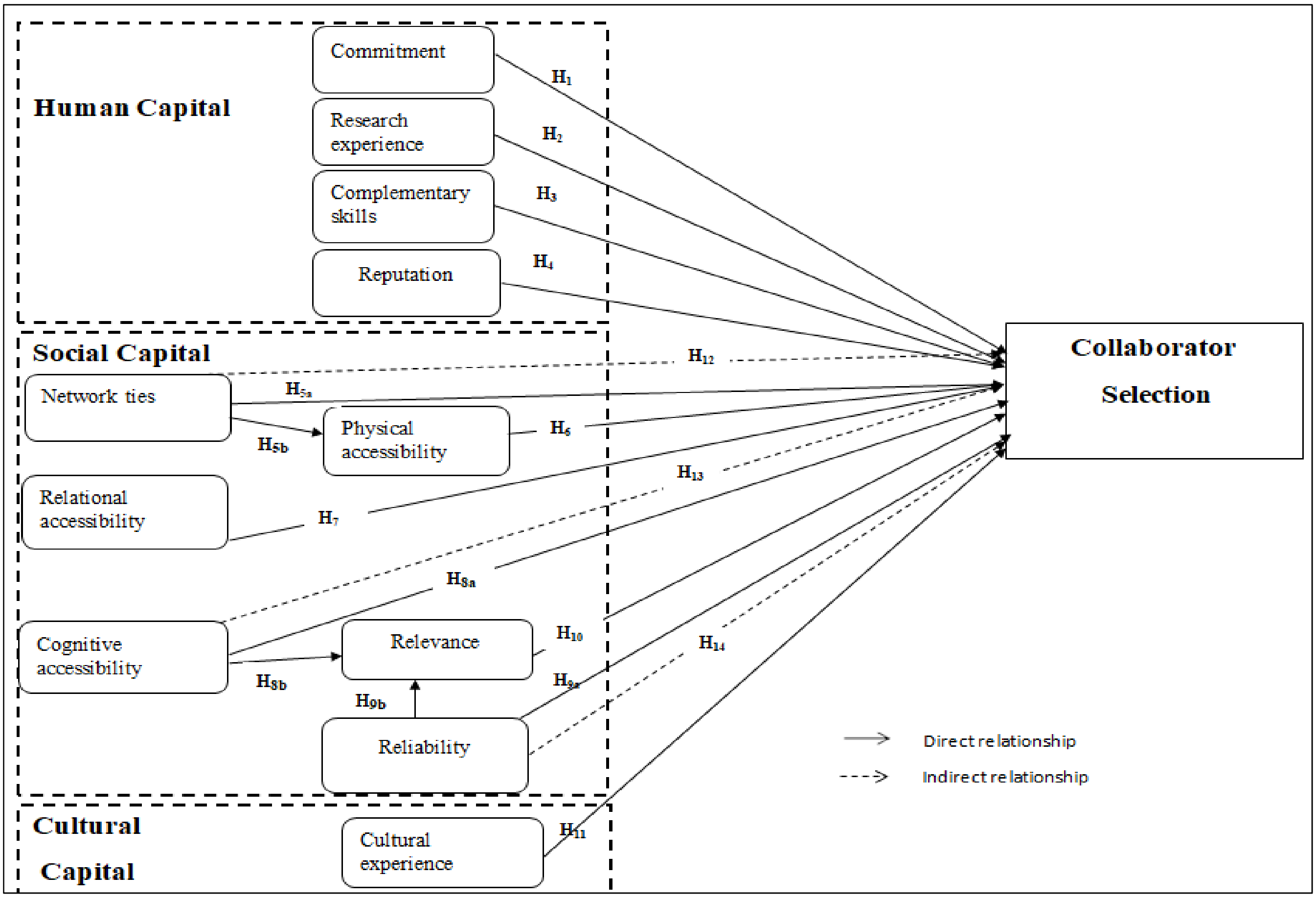

FIGURE 1. **The proposed research model.**

Since research collaboration aims to build knowledge, Nahapiet and Ghoshal [30] developed the SCT arguing that social capital facilitates knowledge development by enabling information exchange. Woudstra *et al.* [62] distinguished two conditions for information exchange, which are accessibility, and the information quality. Moreover, in their model, the authors divided accessibility into three dimensions (physical, cognitive and relational accessibility) and information quality into two dimensions (relevance and reliability). Research collaboration is a process of information exchange. Therefore, in addition to the importance of an individual's network ties in the social capital of the STHC model, information quality and accessibility are also important. Thus, to examine the social capital characteristics of the research collaborator, the social capital model by Woudstra *et al.* [62] has been integrated with the STHC model.

B. THE RESEARCH HYPOTHESES

The proposed model factors have been selected based on the STHC model and SCT and categorized according to STHC model dimensions into three categories: human capital, social capital, and cultural capital factors as presented in Figure 1. The research hypotheses are discussed in following subsections:

1) HUMAN CAPITAL FACTORS

Human capital is essential for knowledge workers who participated in R&D tasks [63]. Research collaboration is considered R&D task. However, human capital is important for research collaboration [1]. Thus, four human capital factors have been selected in this research: commitment, research experience, complementary skills, and reputation.

a: COMMITMENT

Commitment refers to the research collaborator's willingness to give individual time and energy for research collaboration success [64]–[66]. Control theory indicates that commitment is a critical coordinating mechanism for strategic alliances where processes management is challenging. Mat *et al.* [67] found that commitment has a positive effect on collaborator selection between firms. Additionally, Waruszynski [4] studied the factors that lead to effective collaboration during transformational change period based on a qualitative method. Their results indicated that commitment is an important factor for effective collaboration. Moreover, Chen and Goh [68] developed a method for cooperative collaborator selection in the supply chain domain. They found that commitment between collaborators is an important factor and guarantee of high-performance collaboration in supply chain. Therefore, the following hypothesis is proposed:

H1: Commitment positively influences collaborator selection in the research universities context.

b: RESEARCH EXPERIENCE

Research experience refers to the experience of a research collaborator in research [1]. According to the STHC model, individuals collaborating with others contribute unique resources like research experience [50]. Iglič *et al.* [1] found that researchers who participate in several research collaborations acquire more knowledge and skills; their results showed that research experience positively affected research collaboration. Moreover, Birnholtz [69] and Toral *et al.* [70] found that research experiences positively affected interest in future collaborations. In the product development domain, Büyüközkan and Güleryüz [71] found that research experience can reduce the uncertainty concerning the reliability and cooperative capabilities of collaborators. Also, Chaiwanarom and Lursinsap [72] found that senior researchers are more preferable collaborators compared to junior researchers. Moreover, van Rijnsoever and Hessels [73] found that years of research experience is significant for disciplinary and interdisciplinary research collaboration. Therefore, the following hypothesis is proposed.

H2: Research experience positively influences collaborator selection in the research universities context.

c: COMPLEMENTARY SKILLS

It refers to the extent to which a research collaborator has non-overlapping knowledge and skills [71]. Complementary skill is an important human capital factor [49] Büyüközkan and Güleryüz [71] developed a decision-making model for collaborator selection in the product development context. Their results showed that high similarity between the knowledge possessed by companies and their resources leads to collaboration being redundant. Also, Arsenyan and Buyukozkan [74] presented the criteria for CPD collaborator selection, where they defined complementary skills as an important factor for collaborator selection. According to Franco [75], a collaborator should contribute unique knowledge and skills that the other party lacks. Concerning collaboration, both collaborating entities need the other's skills to achieve their goals and tasks [76]. Thus, complementary resources contributed by both collaborators were important for collaboration success. This leads to the following hypothesis:

H3: Complementary skills positively influence collaborator selection in the research universities context.

d: REPUTATION

Reputation relates to a collaborator's position and reputation in research communities as a result of previous research [14]. The reputation of the researcher has been used to predict outcomes and research quality. A research collaborator having a good reputation or strong community standing can significantly influence the success and acceptance of publications and grant proposals. Alternatively, collaborations might fail due to the loss of reputation [77]. Future collaboration opportunities, researchers' careers, and research effectiveness might decline if research collaborators have their papers retracted for reasons like fraud [78]. Researchers prefer to collaborate with other researchers that have good community standing and great reputation [79]. Moreover, Song [80] studied the factors that influence the collaborator selection process outsourcing in the pharmaceutical R&D domain. He found that selecting a collaborator with a good reputation can provide legitimacy and popularity in the market. In their study, Xiao *et al.* [81] stated that reputation is an intangible asset, and it is an important criterion in selecting corporate collaborators. They pointed out that reputation is a risk reduction mechanism because collaborator seeking firms deal only with firms they trust. Thus, collaborating with a reputable collaborator can reduce risk, costs, while providing long-term and stable collaboration. Thus, the following hypothesis proposed:

H4: Reputation positively influences collaborator selection in the research universities context.

2) SOCIAL CAPITAL FACTORS

Social capital helps in creating, transferring, and implementing expertise [82]. According to STHC and SCT that have been chosen as a theoretical foundation in this study, the social capital factors that will be studied in this research are network ties, physical accessibility, relational accessibility, cognitive accessibility, reliability and relevance.

a: NETWORK TIES

Network ties refers to the power of the relationships; represent the motivation that a collaborator seeker has to exchange resources with that collaborator, and the communication frequency between the collaborator seeker and the collaborator [83], [84]. Nahapiet and Ghoshal [30]) found that network ties facilitate resource accessibility, locating valuable information, and decrease the time required for obtaining the required information and expertise. The network ties between the collaborators concerning international scientific collaborations are positively related to collaboration effectiveness [60]. Moreover, Murgia [85] found that in R&D collaborations, frequent interactions between a set of collaborators can create stronger network ties which can provide a shared understanding of ideas and goals. It also can decrease the risk of opportunistic action and information asymmetry. Moreover, Al-Tabbaa and Ankrah [86] showed that the presence of network ties (pre-existing bonds) between the university and industry actors increased the certainty about the capacity and commitment of potential collaborators.

Expert availability may enhance collaboration outcomes, such as collaboration productivity and effectiveness [87] Cornwell and Cornwell [87] found that network ties with experts provided lower cost and in-time access to the experts and their knowledge. Thus, individuals who have network ties with experts are expected to access and benefit more from expert's knowledge compared to strangers [87]. Moreover, Melkers and Kiopa [88] found that network ties allow enhancing physical proximity with others and access to their skills and tacit knowledge. Additionally, Chiu *et al.* [83] stated that more the network ties between knowledge partners, better is the breadth, and the intensity and frequency of the knowledge exchanged. It is costly to acquire knowledge; however, ties between members of a network allow a low alternative for experts. Also, Chiu *et al.* found that network ties affect access to collaborators for integrating and exchanging knowledge. Accordingly, H5a and H5b are as follow:

H5a: Network ties positively influence collaborator selection in the research universities context.

H5b: Network ties positively influence physical accessibility

b: PHYSICAL ACCESSIBILITY

Physical accessibility refers to the degree of effort or amount of time needed to gain access to the research collaborator [14], [62], [89], [90]. Woudstra *et al.* [62] pointed out that the structural dimension of social capital helps expertise seekers to have access to experts in a timely and efficient way. It concerns the effort and duration of the physical activity required to get access to experts. Physical accessibility has been studied by several researchers to examine if it affects expert selection [62], [91]–[96]; their results indicated that physical accessibility has a positive influence on expert selection. Concerning research collaboration, Cummings and Kiesler [97] noted that distributed research projects have higher collaboration cost, and more effort is required to sustain strong working relationships. When collaborators are near each other, they are expected to involve in informal communications more frequently. Stvilia *et al.* [14] addressed that proximity between collaborators can reduce transaction costs, make coordination easy, lead to shared organisational culture, and strengthen trust. Accordingly, the following hypothesis is proposed:

H6: Physical accessibility positively influences collaborator selection in the research universities context.

c: RELATIONAL ACCESSIBILITY

Relational accessibility, also called comfortability by Fidel and Green [95]. It refers to feeling comfortable when working with the research collaborator [62], [94], [95]. For example, when a group has created an amicable and cosy network in which many individuals are friends with others, there is increased comfort. Previous studies in expertise seeking domain, relational accessibility plays a role in selecting an interpersonal knowledge source [62], [94]–[96], [98]. Woudstra *et al.* [62] pointed out that access to experts may be hindered if expertise seekers feel uncomfortable in presenting the limitations of their scope of knowledge on a particular subject to some experts. It is possible that expertise seekers may feel that they are burdening the busy experts, or they do not like the feeling of indebtedness. Thus, expertise seekers expend relational effort-specific costs towards accessing an expert to overcome these negative feelings Iglič *et al.* [1] found that researchers from one department favoured collaborating with individuals from their department; there is lesser trust and potential confrontational issues while working with people from other departments. Furthermore, several studies confirmed that relational accessibility plays a key role in collaborative work [77], [99], [100]. The absence of relational accessibility leads to distrust between the collaborating parties, hampers collaborator selection, makes the collaboration process difficult and affects productivity. In addition to that, Al-Tabbaa and Ankrah [86] pointed out that one of the main issues in collaborative work is relational accessibility which affects trust. Comfort and trust are required for progressive work. Accordingly, the following hypothesis is proposed

H7: Relational accessibility positively influences collaborator selection in the research universities context.

d: COGNITIVE ACCESSIBILITY

Cognitive accessibility refers to understandability and communication with the research collaborator and the processing of the obtained information [62], [91], [92]. Cognitive accessibility is a major driver in research collaborations [101]. Moreover, Hoekman *et al.* [102] stated that collaboration needs sensitivity in communication which is easier if the collaborators speak similar languages. In addition to language, possessing expertise in similar knowledge areas helps collaborators understand each other, whereas collaborators from different cognitive backgrounds may have misunderstandings [103]. Moreover, Steinmo and Rasmussen [48] found that firms with good levels of cognitive accessibility to universities have innovative performance and absorptive capacity in collaborations. Additionally, in the university-industry collaboration context, Bruneel *et al.* [104] pointed out that lack of understandability is a barrier to collaboration.

In the communication context, good communicators are those who can clarify their expressions, avoid ambiguity, and speak in a concise and orderly way. However, the conversation should be simple enough not to impose a cognitive load on the listener. This increases the value and relevance of knowledge exchange. Xu and Chen [42] found that cognitive accessibility has a significant influence on relevance in document retrieval. Therefore, if a research collaborator uses technical language and has background knowledge about the area of study, then such knowledge will be relevant to the collaboration. This leads to the following hypotheses:

H8a: Cognitive accessibility positively influences collaborator selection in the research universities context.

H8b: Cognitive accessibility positively influences relevance.

e: RELIABILITY

Reliability is also known as technical quality, and it refers to research collaborator extensive knowledge about the subject of research area, and the individual should be dependable [36], [62] Fidel and Green [95] stated that an expert is reliable if he/she is consistent and dependable; for instance, selecting an expert because he is ''sets a standard for the industry.'' The reliability of experts concerning information source selection has been studied by several researchers [62], [94], [95]. They found that it positively influenced the expert selection. Moreover, concerning strategic alliance, Wu *et al.* [105] found that reliability has a positive effect on collaborator selection.

The information usefulness is related to relevance and reliability. Hence, users depend on their evaluation of information relevance and reliability in identifying the usefulness of the information for a specific task. In their study Kadous *et al.* [106] found that reliability assessment positively influences the evaluation of relevance in the context of fair value. They stated that unreliable assessment created irrelevant fair value and affected results for decision-makers. Additionally, Xu and Chen [42] found that reliability has a significant impact on relevance in document retrieval. They stated that a user has limited knowledge in a particular area when he/she is searching for additional information. This reasoning implies that if the research collaborator is dependable and can provide reliable information, then the information will be relevant to the collaboration task. This logic leads to the following hypotheses:

H9a: Reliability positively influences collaborator selection in the research universities context.

H9b: Reliability positively influences relevance.

f: RELEVANCE

Relevance refers to the match between the knowledge provided by research collaborator and the research area concerning the research collaboration task [62], [94], [107]. The source is understood to have relevant knowledge if the provided knowledge is useful and relates to the task [42]. The value of exchanged information is associated with its relevance. However, relevance is context-specific and differs across individuals [108]. According to Woudstra *et al.* [62] the parties participating in information exchange should expect value from the information exchange. The value of the exchanged information is directly related to its relevance. Previous researchers who worked on expertise seeking found that information relevance affects expert selection [62], [94], [107]. Wang *et al.* [26] pointed out that expertise relevance is a significant factor for collaborator selection for university-industry collaboration. Thus, the following hypothesis emerges:

H10: Relevance positively influences collaborator selection in the research universities context.

3) CULTURAL CAPITAL FACTOR

Cultural capital is the third dimension in the STHC model. It reflects a scientist's cultural experience, especially across different categories such as gender, race, SES, nationality, and discipline [49].

a: CULTURAL EXPERIENCE

Cultural experience refers to scientists' experiences acquired during their interaction with individuals having different cultural backgrounds [49]. Scientist's experiences such as experiences with different gender, nationality, race, Socioeconomic Status (SES), and discipline. Corley *et al.* [49] mentioned that science and technology research had addressed different cultural dimensions, such as gender, race, and nationality [109]. Also, nationality is important for a scientist's career path Stvilia *et al.* [14] found that collaborator's culture and gender were more significant to participants who had more collaboration experiences than those who have had less experience. Corley *et al.* [49] pointed out that every individual has distinct cultural characteristics (for example, gender, race, SES, nationality, and discipline), and researchers are no exception. Researchers are affected by cultural characteristics when collaborating with other researchers. They often meet and work with collaborators from various socio-cultural backgrounds. This leads to the following research hypothesis:

H11: Cultural experience positively influences collaborator selection in the research universities context.

b: MEDIATING ROLE OF PHYSICAL ACCESSIBILITY AND RELEVANCE

Pena-López and Sánchez-Santos [110] considered social capital as the net- work of relations (network ties) that an individual has and can grant access to assets of resources such as access to network members and their knowledge. Network ties increase physical access to individual resources [87]. Additionally, Chiu *et al.* [83] found that the more network ties between knowledge collaborators allow a low-cost way for them. Moreover, Melkers and Kiopa [88] found that network ties enhance physical accessibility with others and access to their skills and tacit knowledge. Ponds *et al.* [111] found that physical accessibility is the most important factor in research collaboration. Additionally, Stvilia *et al.* [14] addressed that closeness of location between collaborators can reduce transaction costs, make coordination easy, lead to shared organizational culture, and strengthen the trust formation.

According to the previous explanation we notice that network ties can facilitate the physical accessibility to the research collaborators and the physical accessibility is important for collaborator selection. Therefore, the following hypothesis is proposed:

H12: Physical accessibility mediates the relationship between network ties and collaborator selection in the research universities context.

In knowledge exchange, the participating partners should expect value from the information that has been exchanged in information exchange. The value of exchanged information is directly related to its relevance, for which cognitive accessibility is a precondition [62]. Therefore, cognitive accessibility is an important determinant for relevance. Additionally, Xu and Chen [42] found that according to human communication as theoretical foundation, cognitive accessibility and reliability have a significant impact on relevance in documents retrieval. Moreover, cognitive accessibility can improve knowledge quality and relevance through shared languages, ideas, and visions [83]

Information relevance is subjective, for example, people evaluate a message depending on their subjective judgment [112]. This judgment may determine a person's decision to select a particular research collaborator. Thus, we proposed that information relevance perceived by research collaborators can influence their likelihood of their selection. This reasoning implies that if the research collaborator can provide reliable and understandable information, it will be relevant to the collaboration task, and this relevance increases his/her selection opportunity to participate in research collaboration. This logic leads to the following hypotheses:

> H13: Relevance mediates the relationship between cognitive accessibility and collaborator selection in the research universities context.
> H14: Relevance mediates the relationship between reliability and collaborator selection in the research universities context.

III. METHODOLOGY

A. STUDY CONTEXT

This research focuses on developing a collaborator selection model that includes the factors influencing collaborator selection for research collaboration in the research universities context so that the factors can be integrated with the expert finding system. The study was conducted in Malaysian research universities, namely, Universiti Malaya (UM), Universiti Kebangsaan Malaysia (UKM), Universiti Putra Malaysia (UPM), Universiti Teknologi Malaysia (UTM), and Universiti Sains Malaysia (USM). Accordingly, the context of this study is Malaysia, and the population for primary data collection comprises academic researchers in Malaysian research universities who have experience in research collaboration. Malaysian research universities have been selected because they are distinguished from non-research universities in terms of their concentration on research activities and commercialisation [113]. The main concerns for Malaysian research universities are the quantity and quality of researchers and their research, the number and quality of postgraduate enrolments, innovation, professional facilities, and networks. Based on such factors, these universities are prioritised by the government for research grants [114]. Moreover, the ministry of higher education in Malaysia attempts to enhance research and innovation by providing technologies that facilitate research collaboration among academic researchers since the productivity of scientific research is linked with high levels of collaboration [115]. Thus, two of Malaysian research universities, namely, UM and UTM, adopted expert finding systems, which will enhance the process of finding collaborators.

B. UNIT OF ANALYSIS AND SAMPLING TECHNIQUE

In this study, the unit of analysis is focused on the individual level.

There are two main techniques for choosing sample elements: probability and non-probability [116]. In probability sampling every entity in the population has a nonzero chance of selection [117]. In non- probability sampling, a set of techniques is used where an entity selection in the technique is done based on the judgment of the researcher [118]. It is suitable when the number of target population is unknown [119].

This study adopted non-probability sampling for the following reasons. Firstly, as the target population for this study is the academic researchers who have experience in research collaboration and collaborator selection in Malaysian research universities, the number of researchers experienced in research collaboration in the target population is unknown. Secondly, accessing all lecturers in the target universities is not feasible because researchers are busy, and the process is costly and time-consuming. According to Abdelsalam *et al.* [120] and Gobara *et al.* [121], in purposive sampling participants normally selected to achieve a particular purpose. Purposive sampling was selected because this research aims to examine the factors that affect collaborator selection in research universities. The authors designed question in the first section of the questionnaire as criteria for purposive sampling. The question is (have you collaborated with any research collaborator (academic staff only) from your university or other universities during your work in the university?) which is aims to know if the respondent has a previous background in selecting research collaborators or not. If the respondent has no experience in research collaboration, the respondent will be excluded.

Precisely, the required sample size for a particular model should be determined by the power analysis on the part of the model with the largest number of predictors [122]–[124]. Therefore, to ensure the adequacy of the sample size of this study, G* power analysis software [125] was used. According to Dattalo [126], this study's setting was $\alpha = 0.05$ and $\beta = 0.95$ for error type one and two, effect size = 0.15 and 11 independent constructs, as proposed in the research model. The results of G* power analysis showed that the initial sample target for this study is 178 respondents.

C. INSTRUMENT DEVELOPMENT AND VALIDATION

A reliable and valid questionnaire has been developed to test research hypotheses. Concerning questionnaire development, the potentially useful and relevant measurement items for each construct have been extracted from previous research. After that, the selected items were adapted into the context of the study. In this study, the adapted measurement items for constructs are specified in appendix A. A close-ended questionnaire was adapted and includes answer choices where the respondents select the best answer from provided choices [127]. In this research, the respondents were requested to rank each measure on a five-point Likert scale to clarify their view regarding the extent of agreement or disagreement concerning each item statement. The Likert Scale answers ranged from 1 to 5, where 1 = Strongly disagree (SD), 2 = Disagree (D), 3 = Neutral (N), 4 = Agree, 5 = Strongly agree (SA). The survey was divided into two sections, sections A and B. Section A was identified the personal background information of the respondents. These aspects include gender, ethnicity, age, current academic position, number of years being employed as academic staff in the university, and the number of years spent in conducting research. An additional question (have you collaborated with any research collaborator (academic staff only) from your university or other universities during your work in this university?) was added to evaluate if the respondent has a previous background in selecting research collaborators. If the respondent had no experience in collaborator selection, that individual was excluded. Section B provides statements for each construct to test the proposed research model.

After questionnaire development, it was validated by face and content validity, and pilot test. Face validity was conducted by distributing the survey to a group of experts with experience in questionnaire development and information systems research. Face validity aimed to validate whether the instrument appears to make sense, understandable and suitable with the determined time. Subsequently, content validity was conducted. It is about "the extent to which a questionnaire has an accurate sample of measures for the variable being measured" [128]. In this study, a group comprising seven experts from the information systems and other associated domains, including one linguistic expert evaluated instrument content validity. The experts were chosen such that all had experience in research collaboration for a minimum of five projects in order to ensure that they have adequate expertise in research collaboration. Based on the experts' validation results, two items related to reliability and physical accessibility were removed from the measurement model. Additionally, experts recommended revisions for specific items. All the recommendations from the experts were incorporated, and the instrument was considered ready for the pilot study.

A pilot test is "a simulation of survey implementation carried out on a sample chosen from the target population" [127]. The pilot test aims to find out and address the problems or weaknesses in the questions of instrument and instrument layout. Cooper and Schindler [129] conducted a study and suggested that the sample size for the pilot study should be between 25 and 100 individuals. Therefore, 100 survey forms were distributed online to academic researchers in Malaysian research universities (20 for each university). The response rate was significantly low; therefore, an additional 20 paper-based survey forms were distributed to UTM academic researchers. The total of 70 questionnaire was collected. Out of the 70 collected surveys, five surveys were excluded from analysis because the respondents had no research collaboration experience. Smart PLS v3.2.9 was employed to evaluate the measurement model. Validation of the measurement model was performed using three tests: 1) internal consistency, 2) convergent validity, 3) discriminant validity [122]. Convergent validity was evaluated by testing its indicator reliability (factor loading) and Average Variance Extracting (AVE) [122], [124]. The values of factors' outer loading for all the indicators met the threshold (above 0.7), except for two items: complementary skills (COMP1) and network ties (NET5), whose values were 0.665 and 0.392, respectively. Because composite reliability and AVE for complementary skills (COMP1) were above the threshold, COMP1 has been left, whereas network ties (NET5) have been removed because it's outer loading was below 0.4.

Cronbach's alpha (CA) and composite reliability are used to assess internal consistency. Values are considered "acceptable" if they are in the range of 0.60-0.70, "satisfactory to good" in the 0.70-0.90 range, while values of 0.95 and above are problematic; it there indicates that such items are redundant [122], [124]. All values of CA and composite reliability were above 0.06 and less than 0.95.

On the other hand, discriminant validity has been evaluated using cross-lading, Fornell-Larcher criterion, and Heterotrait-Monotrait (HTMT) [122], [124]. The results of cross loading indicated that the item's outer loading for each construct is greater than its loading with other constructs. Moreover, the results of the Fornell-Larcher criterion revealed that the square root of AVE for each construct is greater than its correlations with other constructs. Additionally, all HTMT values are less than 0.85, which means that all constructs in this model are distinct. Thus, the measurement model meets the required criteria for discriminant validity. After instrument development and validation, it was ready for primary data collection.

D. DATA COLLECTION

The process of data collection was conducted using online surveys hosted by SurveyMonkey. The link to the survey was sent through email to 1000 researchers in Malaysian research universities since researchers are typically busy and online survey has a low response rate [114], [130]. Data collection was conducted between June 2019 and September 2019. Two weeks after data distribution, the recipients were reminded to participate. Additional reminder was sent after one month. Moreover, the researcher went to UM, UKM and UPM and requested the university's management office to send the link through email to their researchers. After four months, the total number of the received questionnaires was 449 (45% response rate). From a total of 449, 60 respondents had no previous experience in research collaboration; thus, 389 respondents remained. Collected data must be screened before beginning data analysis. Data screening is the procedure of guaranteeing that the data is clean and prepared for analysis [122]. The important issues that need to be considered during data screening are missing data and outliers. In this study, from a total of 389 respondents, 35 respondents were excluded because the data contained outliers, same answers for different variables, and missing data. Additionally, five respondents were excluded because they were from other universities. Thus, 349 questionnaires were deemed useful for data analysis. The results of G* power analysis showed that the initial sample target for this study is 178 respondents. Therefore, the total number collected for the main data collection (349 respondents) is large enough to test the proposed model variables.

E. DATA ANALYSIS

This research used SEM to test the proposed model. SEM methods are Partial least squares structural equation modelling (PLS-SEM), and Covariance-based structural equation modelling (CB-SEM). Partial Least Squares (PLS) is a component-based SEM method commonly used to model the relationships between dependent and independent variables in IS researches [131]. The PLS can test the relationships between multiple dependent and independent variables plus validity and reliability of latent variables.

In contrast, CB-SEM estimates model parameters by the empirical variance-covariance matrix [132]. This research used PLS-SEM using Smart PLS (v.3.2.9) software as a statistical technique to test the research model, for the following reasons: 1) when the model is complex (contains ten or more constructs, PLS-SEM is more suitable [133]. This research contains 11 constructs. 2) When researchers need more analysis such as IPMA, moderating, and mediating analysis PLS-SEM is the best choice [122], [124], [132]; in this research IPMA should be used to identify the most important factors and mediating effects should be analyzed. 3) PLS-SEM has much greater flexibility compared to CB-SEM [133]. 4) According to [134], CB-SEM suffers from the identification problem; to avoid it each variable should have more than three items. PLS-SEM can be used to conduct fewer items and the identification issue could be avoided. This study contains constructs with three items. Thus, the authors tried to avoid the CB-SEM identification problem. 5) PLS-SEM has user-friendly software packages [134] and CB-SEM was the dominant until around 2010, but in recent years, the number of published articles using PLS-SEM increased significantly compared to CB-SEM [122].

The data analysis in this study was conducted in two steps based on Hair Jr *et al.* [122]: 1) measurement model evaluation, and 2) structural model evaluation. The results of data analysis are presented in the next section.

TABLE 1. Demographic information.

Demographic Information	Frequency	Percentage
Gender		
Male	147	42
Female	202	58
Ethnicity		
Malay	287	82
Chinese	27	8
Indian	11	3
Other	24	7
Age		
Less than 25 years	1	0
26 – 30 years	7	2
31 – 35 years	64	18
36– 40 years	65	19
41 – 45 years	60	17
45 years and above	152	44
Current Academic Position		
Professor	35	10
Associate Professor	75	22
Senior lecturer	204	58
Lecturer	35	10
Number of years employed as academic staff in the university		
Less than 5 years	85	24
5 - 10 years	63	18
11 - 20 years	111	32
20 and above	90	26
How long have you been conducting research?		
Less than 5 years	46	13
5 - 10 years	139	40
11 - 20 years	112	32
20 and above	52	15
When you select a research collaborator, which criteria is your choice one based on?		
My own opinion	332	95
My university has criteria for collaborator selection	17	5
Your University		
UKM	63	18%
UM	54	16%
USM	81	23%
UPM	77	22%
UTM	74	21%

IV. RESULTS

A. DEMOGRAPHIC BACKGROUND

Table 1 presents the respondents' demographic information concerning the primary data collection. It should be noticed that 58% of the respondents were female, while 42% were male. 98% of the respondents are more than 30 years old. Most of the respondents were senior lecturer 58%, followed by associate professor 22% and the least were professor and lecturer 10%. Moreover, 76% of the respondents have more than five years of experience as academic staff, while 24% have less than five years of experience. Also, a majority of the respondents (87%) had more than five years of experience in conducting research; thus, the respondents have immense knowledge about collaborator selection. The majority of the respondents (95%) select collaborators based on their criteria, and only 5% select collaborators based on predefined criteria. That 5% was from USM, UPM, UKM, and UTM. Their criteria comprised collaborator reputation, university ranking, collaborator being from a research university, the mixed academic position of the collaborator, different school or department, publications, and H-Index. This indicates that some research projects might require collaborator selection criteria; however, universities have no criteria.

B. STRUCTURAL EQUATION MODELING (SEM)

1) EVALUATION OF THE MEASUREMENT MODEL

As discussed in the research methodology, measurement model validation has been conducted in this study using three tests: internal consistency test, convergent validity test, and discriminant validity test.

a: CONVERGENT VALIDITY

It refers to "the degree to which an item correlates significantly with alternative items of the identical variable" [122]. Convergent validity assessment was conducted using the indicator reliability (factor loading) and Average Variance Extracting (AVE) [122], [124]. In this study, the results of the outer loading of the factors are shown in Table 2. The values of all the indicators have met the threshold (>0.7). The second measure for convergent validity assessment is AVE. The standard value for AVE is 0.50 or above; accordingly, in this study, AVE values for all constructs exceeded the required threshold, as shown in Table 2.

b: INTERNAL CONSISTENCY RELIABILITY

It has been evaluated by Cronbach's alpha (CA) and composite reliability. Values are considered "acceptable" if they are in the range of 0.60-0.70, "satisfactory to good" in the 0.70-0.90 range, while values of 0.95 and above are problematic; it there indicates that such items are redundant [122], [124].

In this study, CA and composite reliability were examined using the PLS algorithm in Smart PLS. Table 2 indicates that all values of CA and composite reliability are above the threshold, and no construct has CA and composite reliability greater than 0.95.

c: DISCRIMINANT VALIDITY (DV)

it has been defined as "the extent to which a given variable differs from other variables" [122]. In this research, discriminant validity has been evaluated using cross-lading, Fornell-Larcher criterion, and HTMT. The results of cross loading indicated that the item's outer loading for each construct is greater than its loading with other constructs. Moreover, the results of the Fornell-Larcher criterion revealed that the square root of AVE for each construct is greater than its correlations with other constructs. Furthermore, HTMT values are all less than 0.85, which means that all the constructs are distinct as it shown in Table 3.

2) EVALUATION OF THE STRUCTURAL MODEL

Structural model evaluation was performed according to Hair Jr *et al.* [122]. It contains collinearity assessment, evaluating the significance and relevance of the structural model relationships, evaluating the mediating effects of relevance and physical accessibility that have been proposed in the research model, evaluating level of R2, evaluating f2 effect size, and evaluating predictive relevance Q2. Structural model evaluation has been performed using the PLS algorithm and resampling technique (bootstrapping).

a: COLLINEARITY AND COMMON METHOD BIAS TEST

Collinearity assessment conducted by computing the Variance Inflation Factor (VIF) and tolerance (TOL). Variance Inflation Factor (VIF) is "the degree of increase in the standard error due to the occurrence of collinearity" [122]. It is reciprocal of the tolerance VIF = 1/TOL [122]. Based on the work of Hair Jr *et al.* [122], the tolerance value should be greater than 0. 20 and VIF should be less than 5. In this study, the assessment of collinearity was performed using IBM SPSS. The predictor constructs were assessed separately for each dependent construct. The results of collinearity assessment are shown in Table 4 and reveal that there was no collinearity concern in the proposed research model. Thus, the constructs were not correlated and that no construct should be removed from the proposed research model.

Common method bias tested based on the results of VIFs. As stated by Kock [135], Bag *et al.* [136], Hameed *et al.* [137], Kim *et al.* [138], when using PLS-SEM, the common method bias cab be tested from the results of full collinearity test; if all VIFs values are equal to or less than 3.3, this indicates the model is free of common method bias. The study results of VIF values in table 4 show that all VIF values were less than 3.3, which indicates there was no contamination of common method bias. Therefore, common method bias was not a problem.

b: STRUCTURAL MODEL PATH COEFFICIENTS

It evaluated by four tests based on [122]; 1) T value: which relies on the standard error. When the t value is greater than the threshold value, it means that the path coefficient is significant at a certain significance level. The threshold T values that are normally used for two-tailed tests are 1.65, 1.96, and 2.57 when the significance levels are 10%, 5%, and 1%, respectively. 2) P-value: it is the probability of rejecting a true null hypothesis erroneously. When significance level = 10%, p-value must be < 0.1, at significance level = 5%, p-value must be < 0.05 and at significance level = 1%, p-value must be < 0.01. 3) Confidence Interval (CI): it offers information on the estimated coefficient's stability by providing a range of possible population values for the construct based on the variation in data and the

TABLE 2. Measurement model tests results.

Latent Variable	Indicator	Convergent Validity		Internal Consistency Reliability		DV
		Loading >0.70	AVE 0.50	Composite Reliability 0.6-.90	CA 0.6-.90	HTMT does not include 1
Cognitive accessibility	COGA1	0.856	0.768	0.943	0.924	Yes
	COGA2	0.890				
	COGA3	0.909				
	COGA4	0.892				
	COGA5	0.832				
Collaborator Selection	COLS1	0.739	0.679	0.863	0.760	Yes
	COLS2	0.849				
	COLS3	0.877				
Commitment	COMM1	0.870	0.775	0.912	0.854	Yes
	COMM2	0.897				
	COMM3	0.873				
Complementary skills	COMP1	0.906	0.796	0.940	0.914	Yes
	COMP2	0.889				
	COMP3	0.901				
	COMP4	0.872				
Cultural Experience	CULE1	0.926	0.836	0.949	0.949	Yes
	CULE2	0.924				
	CULE3	0.938				
	CULE4	0.870				
	CULE5	0.912				
Network ties	NET1	0.834	0.681	0.895	0.844	Yes
	NET2	0.852				
	NET3	0.811				
	NET4	0.803				
Physical accessibility	PHA1	0.887	0.790	0.938	0.912	Yes
	PHA2	0.893				
	PHA3	0.887				
	PHA4	0.890				
Relational accessibility	RELA1	0.859	0.766	0.907	0.846	Yes
	RELA2	0.912				
	RELA3	0.853				
Reliability	RELIA1	0.837	0.682	0.895	0.845	Yes
	RELIA2	0.807				
	RELIA3	0.820				
	RELIA4	0.839				
Relevance	RELV1	0.793	0.612	0.863	0.789	Yes
	RELV2	0.810				
	RELV3	0.786				
	RELV4	0.738				
Reputation	REP1	0.844	0.733	0.892	0.821	yes
	REP2	0.881				
	REP3	0.842				
Research experience	RESE1	0.880	0.768	0.943	0.925	yes
	RESE2	0.888				
	RESE3	0.874				
	RESE4	0.871				
	RESE5	0.869				

sample size. It is based on standard error and identifies the range in which the true population parameter will fall with a specific confidence level. The construct has a significant effect if a confidence interval for the path coefficient does not contain zero. 4) Path coefficient: which ''denotes the hypothesised relationships between the structural model's variables [122]. It has standard values between -1 and $+1$ [122]. The path coefficient values close to $+1$ indicate

TABLE 3. Discriminant validity (HTMT Ratio).

Construct	CULE	COGA	COLS	COMM	COMP	NET	PHA	RELA	RELV	RELIA	REP	RESE
CULE												
COGA	0.189											
COLS	0.436	0.759										
COMM	0.221	0.441	0.676									
COMP	0.170	0.367	0.415	0.202								
NET	0.198	0.500	0.639	0.356	0.299							
PHA	0.260	0.495	0.684	0.441	0.184	0.551						
RELA	0.172	0.367	0.263	0.100	0.258	0.248	0.205					
RELV	0.281	0.588	0.84	0.466	0.226	0.546	0.464	0.212				
RELIA	0.141	0.504	0.687	0.397	0.091	0.424	0.360	0.111	0.628			
REP	0.289	0.186	0.255	0.068	0.182	0.188	0.089	0.231	0.157	0.151		
RESE	0.164	0.338	0.520	0.303	0.088	0.285	0.337	0.139	0.431	0.329	0.064	

TABLE 4. Hypotheses testing.

Hypothesis	Path	Std Beta	t-value	p-value	95% CI	f2	VIF
H1	Commitment → Collaborator Selection	0.171	4.159	p< .001	[0.091, 0.253]	0.075	1.361
H2	Research Experience → Collaborator Selection	0.106	2.503	0.012	[0.027,0.193]	0.032	1.236
H3	Complementary skills → Collaborator Selection	0.124	3.624	p< .001	[0.055, 0.191]	0.045	1.201
H4	Reputation → Collaborator Selection	0.042	1.472	0.141	[-0.016,0.096]	0.005	1.127
H5a	Network ties → Collaborator Selection	0.05	1.426	0.154	[-0.019,0.117]	0.005	1.569
H5b	Network ties → Physical accessibility	0.487	8.96	p< .001	[0.370, 0.582]	0.311	1
H6	Physical accessibility → Collaborator Selection	0.167	3.734	p< .001	[0.080, 0.256]	0.062	1.58
H7	Relational accessibility → Collaborator Selection	-0.03	1.011	0.312	[-0.085,0.030]	0.003	1.179
H8a	Cognitive accessibility → Collaborator Selection	0.181	3.319	0.001	[0.070, 0.279]	0.062	1.863
H8b	Cognitive accessibility → Relevance	0.344	6.323	p< .001	[0.235, 0.445]	0.147	1.249
H9a	Reliability → Collaborator Selection	0.159	3.273	0.001	[0.068,0.259]	0.058	1.53
H9b	Reliability → Relevance	0.36	7.599	p< .001	[0.262,0.451]	0.162	1.249
H10	Relevance → Collaborator Selection	0.24	4.858	p< .001	[0.143,0.337]	0.113	1.781
H11	Cultural experience → Collaborator Selection	0.133	3.759	p< .001	[0.067, 0.205]	0.053	1.178

strong significant relationships (and vice versa for negative values).

The bootstrapping test results revealed that t values, p values, confidence interval, and path coefficient for H1, H2, H3, H5b, H6, H8a, H8b, H9a, H9b, H10, and H11 were supported. Surprisingly, H4, H5a, and H7 were not supported. Figure 2 shows path coefficients and P value and Table 4 summarizes the statistical results of each hypothesis.

c: COEFFICIENT OF DETERMINATION (R^2)

It is defined as a "degree of the predictive power of the model and is computed as the squared correlation among particular dependent constructs actual and predicted values" [122]. As recommended by Urbach and Ahlemann [139], Chin [140] values 0.670, 0.333, and 0.190 are considered substantial, moderate, and weak, respectively. In this study, PLS algorithm analysis was performed to determine R^2 for all independent constructs. Results revealed that R^2 for collaborator selection is 0.715 which means that 72% of the variance in collaborator selection was explained by its independent constructs (cognitive accessibility, reliability, relevance, physical accessibility, commitment, complementary skills, research experience, and cultural experience). Additionally, R^2 for network ties is 0.24, which indicates that network ties explained 24% of the variance in physical accessibility.

Moreover, R^2 for relevance is 0.36, which means that 36% of the variance in relevance was explained by cognitive accessibility and reliability. R^2 values for all dependent constructs of the model exceeded the threshold value (.190). Thus, the research model provides adequate predictive power for collaborator selection in the research universities context.

d: EFFECT SIZE f^2

It is used to assess each construct's substantive impact on the model. Hair Jr *et al.* [122] claimed that in addition to

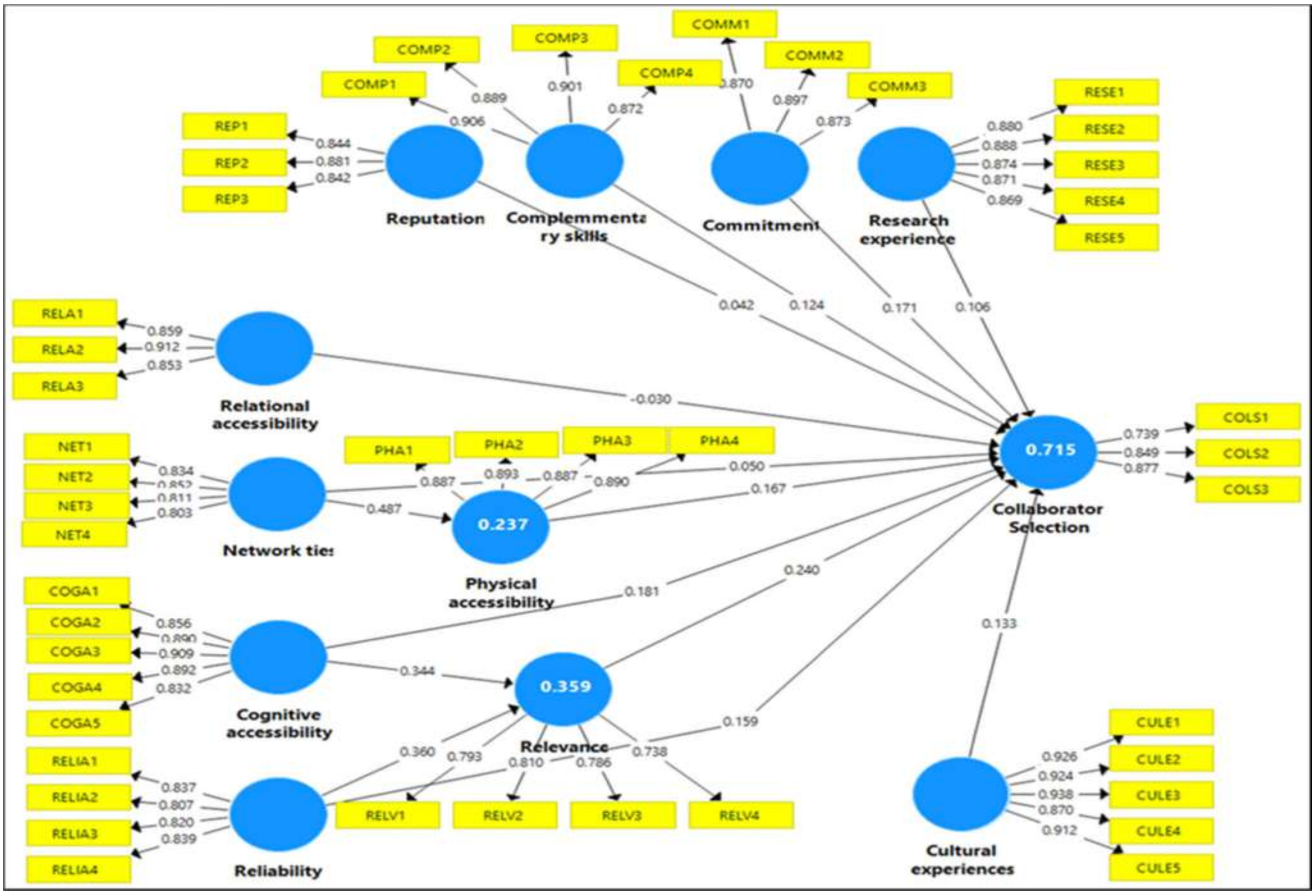

FIGURE 2. Path coefficients and P value.

assessing the R^2 values of all dependent variables the change in R^2 values when one independent variable is removed from the model could estimate the effects of the omitted variable on the dependent variables. Based on the guidelines of Hair Jr *et al.* [122], f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. Effect size values lower than 0.02 imply no effect. In this study, the effect size was calculated according to Hair Jr *et al.* [122] formula, and Table 4 shows the effect size for the research model. The results of effect size revealed that among the factors that were influencing collaborator selection; relevance had medium effect size, and cognitive accessibility, reliability, physical accessibility, cultural experience, commitment, complementary skills, and research experience had small effect size, whereas, relational accessibility, network ties, and reputation had no effect size as their relationships were not significant. Considering relevance as a dependent construct, cognitive accessibility, and reliability had a medium effect size. Considering physical accessibility as a dependent construct, network ties had a large effect on physical accessibility.

e: PREDICTIVE RELEVANCE Q^2

it is used as a ''measure of the out-of-sample predictive power or predictive relevance of the model'' [122]. As suggested by Hair Jr *et al.* [122], Q^2 values should be higher than zero for a particular dependent variable to indicate predictive accuracy of the structural model for a particular dependent variable. The findings showed that Q^2 values for all the dependent constructs are considerably greater than zero (collaborator selection, physical accessibility, and relevance were 0.45, 0.174, and 0.204 respectively). The results indicate that the path model has predictive relevance concerning all three dependent constructs.

f: MEDIATORS EVALUATION

Mediation happens when a third mediator variable interferes between two other related variables [122]. In this study, the significance of mediating effects was assessed by using the bootstrapping procedure and mediation analysis procedures proposed by Hair Jr *et al.* [122]. The procedures suggest three types of mediation: 1) Complementary-partial mediation, in which both indirect and direct relationship are significant and point in the same direction; 2) Competitive-partial mediation, in which both indirect and direct relationship are significant and point in the opposite direction; 3) Full mediation, also called Indirect-only mediation, in which the indirect relationship is significant, the other is not.

In this study, the authors assessed: 1) the indirect relationship between network ties and collaborator selection through physical accessibility (H12), as researcher suggested that

TABLE 5. Mediation results.

Hypothesis	Direct effect	t-value	p-value <0.05?	95% CI	Indirect effect	t-value	p-value <0.05?	95% CI	Mediation type
H12	0.050	1.426	No	[0.019,0.117]	0.081	3.602	Yes	[0.039,0.128]	Full-mediation
H13	0.181	3.319	Yes	[0.070,0.279]	0.082	3.221	Yes	[0.039,0.137]	Complementary- partial mediation
H14	0.159	3.273	Yes	[0.068,0.259]	0.086	5.142	Yes	[0.054,0.119]	Complementary- partial mediation

network ties positively influence physical accessibility (H5b) and physical accessibility positively influence research collaborator selection (H6); 2) the indirect relationship between cognitive accessibility and collaborator selection (H13); as suggested that cognitive accessibility positively influence relevance (H8b) and relevance positively influence research collaborator selection (H9); and 3) the indirect relationship between reliability and collaborator selection (H14); as proposed that reliability positively influence relevance (H9b) and relevance positively influence research collaborator selection. As shown in Table 5, all the mediation relationships were significant. The indirect relationship between cognitive accessibility and collaborator selection (H13) and between reliability and collaborator selection (H14) are of the complementary-partial mediation type. On the other hand, the indirect relationship between network ties and collaborator selection (H12) is of the full-mediation type.

g: IMPORTANCE-PERFORMANCE MAP ANALYSIS (IPMA)

In IPMA analysis, a specific construct's total effect contrasts with the average latent variable scores of the construct's predecessors [122]. The total effect represents the constructs' importance in shaping the target construct, while their average construct scores represent their performance. The main goal of conducting IPMA is to identify the constructs with relatively high importance for the target construct [122]. In this study, it is important to identify the most important factors for collaborator selection, which should be considered when designing expert finding systems.

Based on Ringle and Sarstedt [141], three requirements need to be met to run an IPMA test. First, the rescaling of the construct scores from 0-100 requires all the items to use the metric scale. Second, all the items should have the same scale direction, with the minimum value representing the worst result; the maximum represents the best result. For instance, 1 = strongly disagree and 5 = strongly agree. Third, all the measurement model outer weights estimates must be positive, regardless of the model being formative or reflective.

As a point of departure, all the requirements for performing the IPMA test were met. The setting for deploying IPMA was set. Subsequently, the IPMA test was performed. The results indicated that cognitive accessibility has the highest importance for collaborator selection. The total effect of cognitive accessibility on collaborator selection was approximately 0.263. Precisely, cognitive accessibility is the most important factor for the collaborator selection decision.

A one-point increase in cognitive accessibility performance increases collaborator selection decisions by the value of cognitive accessibility's total effect (0.263). The second important factor was reliability with a total effect of 0.246, while the third important factor was relevance with a total effect of 0.24. The fourth and fifth important factors are commitment, and physical accessibility with total effect of 0.171, and 0.167, respectively. The sixth and seventh important factors are cultural experience and network ties with approximately the same total effect of 0.133 and 0.131, respectively. Finally, the eighth and ninth important factors are complementary skills with the lowest total effects of 0.124 and 0.106, respectively.

V. DISCUSSION

This study proposed a theoretical model for collaborator selection in universities based on the STHC model and the social capital theory; this model should be integrated with the current expert finding systems. The proposed model includes human capital, social capital, and cultural capital factors that influence collaborator selection. The results showed that commitment significantly affects collaborator selection for research collaboration in the university context, and it is consistent with [68]. According to Tarusikirwa and Mafa [142], failure to make commitments often leads to collaboration failure. Thus, this research suggests that the researchers concentrate on commitment as an important factor when selecting their collaborators because committed collaborators will prioritise collaboration tasks. Additionally, research experience positively affects collaborator selection, and this result is consistent with [1], [72]. However, a researcher with higher experience can become more productive and publish more frequently [143]. Moreover, the findings indicate that complementary skills positively affect collaborator selection. This result is consistent with the results of prior studies [68], [74], [144], [145]. Iglič *et al.* [1] addressed that broader specialisation motivates scholars to collaborate in extremely competitive research environments with others who have complementary skills.

Surprisingly, this study revealed that there is an insignificant relationship between reputation and collaborator selection Stvilia *et al.* [14] found that reputation does not affect collaborator selection. The authors' analysis showed that senior researchers were not targeting collaborators based on prestige or reputation. Researchers who have many publications and projects cared more about the collaborator's personality and quality of ideas. However, 47% of the respondents of this study have more than ten years of experience in conducting research. Therefore, they would not pay significant attention to reputation when selecting their research collaborator.

Moreover, network ties have an insignificant impact on collaborator selection. according to the work of van Rijnsoever *et al.* [146], the scientific network activity of researchers first increases and then decreases after about 20 years. Therefore, a researcher may become more independent after several years. The knowledge provided by the network is integrated with the researcher's knowledge base, which eliminates the need to continuously use the network, and he/she can collaborate with any researcher. In this research, 26% of the respondents have more than 20 years of experience in universitie; therefore, this may be a reason for the lesser significance of network ties. According to Melkers and Kiopa [88], another explanation is that the increasing growth in national and international research collaborations motivates researchers to reach outward to new researchers to acquire new knowledge and resources that are not accessible to their colleagues with whom they have strong ties. Although network ties had an insignificant effect on collaborator selection, it has a significant indirect effect on collaborator selection through physical accessibility.

Physical accessibility had a positive effect on collaborator selection. The result is consistent with previous studies [14], [51], [111], [147]. Contrary to our expectation, the results revealed that relational accessibility had an insignificant effect on collaborator selection. One possible explanation could be that researchers can collaborate with other researchers as a result of their skills, research experience, commitment, and accessibility of researchers, regardless of a feeling of comfort with such people. Another possible explanation is that relational accessibility is not essential in collaboration projects having relatively less risk Chiu *et al.* [83] mentioned that relational accessibility becomes significant only in potentially risky situations.

Furthermore, results regarding cognitive accessibility showed high significance and positive impact on collaborator selection. It indicates that cognitive accessibility is the most important factor for enhancing expert finding systems for collaborator selection task in the university context. This result is consistent with previous research [104], [148], [149]. Also, our findings showed that reliability had a positive effect on collaborator selection. This result is consistent with previous studies [62], [105]. According to Zimmer and Henry [150], individuals place a high level of trust in reliable information when they exchange knowledge. Thus, reliability is an essential factor for knowledge exchange. Research collaboration is about knowledge exchange. Therefore, it is anticipated that reliability is considered a significant factor for selecting research collaborators. Additionally, as it has been predicted, relevance significantly influences collaborator selection. This result is consistent with previous studies [26], [39], [151]. Cultural experience also had a significant relationship with collaborator selection.

The results showed that social capital factors (namely, cognitive accessibility, reliability, and relevance) are the most significant factors that influence collaborator selection. Moreover, the research examined the mediating effects of relevance and physical accessibility that have been proposed in the theoretical research model. Mediation analysis indicates that the structural model reveals significant mediating relationships. The results showed that the constructs (cognitive accessibility and reliability) have complementary- partial mediation on collaborator selection, while network ties have a full-mediation effect on collaborator selection.

VI. RECOMMENDATIONS FOR STAKEHOLDERS

This study provides recommendations for expert finding system designers, research collaborators, researchers, and universities. The following subsections present these recommendations.

A. RECOMMENDATIONS FOR EXPERT FINDING SYSTEM DESIGNERS

We recommend expert finding system designers to personalise the retrieval process by giving users the chance to specify their criteria for collaborator selection, which should be as a template for choosing the appropriate data sources. Then, systems designers should extract expertise information from different expertise sources, such as university homepages, title, abstracts, and text from documents, messages from social networks, web activities (like posts on question-and-answering and forums communities), and associations between people on social networks [31] to guarantee complete data. Additionally, based on the results of this study, we recommend stakeholders to combine human capital, social capital and cultural capital factors with expert finding systems for collaborator selection task in the research universities context. Social capital factors (cognitive accessibility, reliability, and relevance) appeared to be the most important factors for collaborator selection, followed by a commitment to human capital factors. Physical accessibility, cultural experience, network ties, complementary skills, and research experience are also important. We recommend expert finding system designers to integrate each factor as sub-criteria like what we suggest for each construct. Guidelines about how to integrate each factor are provided below:

1) COGNITIVE ACCESSIBILITY

We recommend the designers of expert finding systems to integrate this factor as sub-criteria such as collaborator can communicate, the collaborator can convince, the collaborator can explain, and his explanation is understandable. Moreover, expert finding system interface should display the languages spoken by the collaborator. This information can be extracted from his/her previous collaborations; for example, collaborator seekers fill evaluation forms for every collaborator after his/her collaboration period. Then these forms can be analysed, and the required information can be extracted. Additionally, information related to cognitive accessibility can be extracted from lecturers' annual evaluation forms. Students are required to fill these forms after they complete a course. The form contains a section about the degree of their understandability from a particular lecturer. Thus, if students understand well from a particular lecturer, then collaborator seeker can understand too.

2) RELIABILITY

Hofmann *et al.* [34] proposed a system to find similar experts in universities, and they modelled reliability based on a long record of publication, or academic position in the university. Therefore, as an example, expert finding system designers can integrate reliability as follows: collaborator having dependable knowledge can be modelled using the academic position, comprehensive knowledge can be modelled by the number and quality of publications, criteria of at least five years' experience in the area of collaboration can be extracted from the publications. Expert finding systems designers can extract the required information for reliability modelling from collaborator documents, profile, and evaluation forms from previous collaborations [20]. Moreover, they can add a rating feature to represent the reliability of the collaborator. This feature allows collaborator seekers to rate a collaborator on a five-star scale [36].

3) RELEVANCE

All the previous studies regarding expert finding systems considered relevance as the most important factor for expert finding. Surprisingly, this study found that cognitive accessibility and reliability are more important than relevance, and they have a significant effect on relevance. Thus, we recommend expert finding system designers to consider cognitive accessibility and reliability when they model relevance and not depend only on the relevance between the query topic and collaborator knowledge. We recommend that the relevance between the knowledge provided by the research collaborator and the research area for the collaboration task can be modelled as sub-criteria, the relevance of collaborator's documents to the collaboration topic, relevance of collaborator's broad knowledge to the research collaboration topic, and the relevance of collaborator's research interests to the collaboration topic. The information required for modelling relevance can be extracted from collaborator's documents, profile and academic and social networks, such as Google scholar and LinkedIn.

4) PHYSICAL ACCESSIBILITY

Collaborator accessibility and availability are important criteria for collaborator selection, especially in a big organisation where collaborators are geographically dispersed and stay in different time zones. Thus, expert finding system interface should display the local time specific to an individual, location and communication media, such as phone, email, and social media to show their possible availability and accessibility. Moreover, expert finding systems should allow collaborators to set their online status to available, busy or offline [20]. The required information can be extracted from collaborator's previous collaboration evaluation form to clarify if the collaborator is easily accessible. Moreover, they can extract the relationships between collaborator seekers and collaborators from social and academic networks. Accordingly, if there is a strong relationship, then they can easily contact each other.

5) NETWORK TIES

In this study, network ties have an indirect relationship with collaborator selection. We recommend expert finding system designers to combine network ties to facilitate the physical accessibility to collaborators. For example, if a collaborator seeker has a strong relationship with a particular collaborator, he/she can easily access him/her face-to-face or through communications technology Gao *et al.* [152] proposed similarity model to recommend review experts to projects based on their relationships. Their model aims to find the partner relationship between experts. The required information for network ties modelling can be extracted from social and academic networks and relations based on co-authors of publications [20].

6) COMMITMENT

It is the most important human capital factor in this study. Expert finding systems should provide collaborator seekers with information about the degree of collaborators' commitment. For example, collaborators provide the necessary time to accomplish the goals, the collaborator has a sense of belonging to the collaboration, and the collaborator gives priority to the collaboration. This information can be extracted from collaborator's previous collaborations and annual evaluation forms concerning lectureship.

7) COMPLEMENTARY SKILLS

Expert finding systems for collaborator selection should have the ability to retrieve collaborators with complementary skills. Expert finding system designers can use topic models that represent the probable expertise related to a research collaborator through a brief word-based representation of the collaborator's productions. These models can be used to compare collaborators and identify those with similar and different expertise [31]. Accordingly, collaborator seekers can select those who have complementary skills. For example, a data mining collaborator could collaborate with a social commerce expert. To accomplish this goal, expert finding system designers can create a grant database related to content similarity and the collaboration network that can help recommend collaborators with different areas of expertise.

8) RESEARCH EXPERIENCE

It can be represented in expert finding systems as the number of years since the publication of the first scientific work, number of years in supervisory roles, number of years since his/her appointment in the university, the total number of publications, and the total number of collaboration projects. Expert finding system designers can use collaborator's profile, publications, and social and academic networks to extract this information.

9) CULTURAL EXPERIENCE

Expert finding systems designers should integrate collaborators' experiences that they gain from interaction with collaborators from diverse cultural backgrounds. Experiences with same and different gender, race, socio-economic status (SES) (income, education, and occupation), nationality, and discipline are some examples. This information can be extracted from collaborator's profile, previous collaboration forms, and social and academic networks.

B. RECOMMENDATIONS FOR RESEARCH COLLABORATORS

We recommend that research collaborators update their profiles regularly and share their expertise information. Various expertise sources could be used, e.g., homepages, publications, research descriptions, course descriptions, social networks, project/grant repositories, supervised student theses, citation indexes, and movies [21]. This information can be collected from staff homepages and social networks if they are updated. Incomplete data could lead to wrong decisions concerning collaborator selection. Expert finding systems evaluate and retrieve collaborators according to available data [20]. Thus, data availability for collaborators increases their selection chance. Additionally, collaborators should do their best during the research collaboration because their selection for future collaborations depends on their success in the previous collaborations [20].

C. RECOMMENDATIONS FOR RESEARCHERS

Effective collaboration largely depends on the characteristics and skills of the collaborators. Researchers need to collaborate, but the problem is with whom they can collaborate [9]. Impulsive selection of collaborators might decrease the collaboration productivity and increases the risk of project failure. Thus, we recommend researchers to select appropriate collaborators according to the predefined criteria. Additionally, researchers should give feedback and rate a collaborator's competency level after collaboration. This feedback and rating information can be used effectively by expert finding system designers to find a potential collaborator for collaboration seekers [20].

D. RECOMMENDATIONS FOR UNIVERSITIES

Without a clear understanding of the criteria for collaborator selection, collaborator seekers and universities will continue to be vulnerable to wrong decisions. Thus, we recommend universities to adopt these criteria as a strategy for collaborator selection and train their researchers on how to use expert finding systems to make the best possible decision regarding collaborator selection. Additionally, universities are recommended to motivate their researchers to update their profiles regularly. Moreover, universities should identify the benefits of expert finding systems; if collaborators perceive value from expert finding systems, they will use these systems and provide the required personal information [21]. Additionally, privacy-preserving techniques should be developed, and collaborators should be given adequate control over the storage and use of their information.

VII. CONTRIBUTION

The contribution of this study is divided into theoretical and practical perspectives.

Theoretically, this study provides a collaborator selection model for expert finding systems for universities. The proposed research model integrated the STHC model and the social capital theory. The comprehensive literature review showed that the integration of these theoretical models had not been applied in either expert finding systems or collaborator selection research. Although numerous studies investigated research collaboration, far less attention has been paid on collaborator selection with a robust theoretical model. Thus, proposing a collaborator selection model for expert finding systems in university based on the STHC model and social capital theory is a significant contribution.

Moreover, this research is considered to be one of the first studies focused on human capital, social capital and cultural capital factors that influence collaborator seekers' decision to select a particular collaborator in the research universities context. However, there are a limited number of studies on how collaborator seekers select research collaborators and the factors that influence their decision making [14], [43]–[46]. Bozeman *et al.* [44] studied the influence of career stage, gender, and work-style fit on collaborator selection. Corley and Sabharwal [46] found that collaborator name and country of residence are important characteristics for research collaborators. Moreover, Bozeman *et al.* [43] indicated that the collaborator's gender, age, national origin, and degree of study as personal factors and the field of training, and work experience as human capital factors are important for research collaborators. Furthermore, Gunawardena [45] found that job rank, research interest, and institution type specific to the research collaborators influence their selection. Additionally, Stvilia *et al.* [14] examined the influence of resources, cost of tasks, culture, and collaborator personality on selection decision. As discussed above, previous researchers have examined three human capital factors. Along similar lines, Iglič *et al.* [1] stated that human capital is important for research collaboration. Thus, the influence of additional human capital factors for collaborator selection should be examined. Furthermore, research collaboration is about knowledge exchange, which is a social process that needs individual interactions [47]. Therefore, individual relationships are crucial for information exchange. Social capital is essential for successful collaboration [48]. The influence of social capital factors on collaborator selection was not studied in previous studies. In addition to human and social capital, cultural capital appears to have a critical role in collaborator selection [49], and it is often the most challenging barrier to overcome [4]. None of the previous studies examined the effect of cultural capital on collaborator selection.

Furthermore, current studies in expert finding systems identify collaborators based on the relevance between the user query and the documents related to the collaborators. Concerning document retrieval, Xu and Chen [42] found that cognitive accessibility and reliability are also determinants of relevance. Hence, no previous study examined the effect of collaborator reliability and cognitive accessibility on relevance. This study examined the mediating effect of relevance on collaborator selection. The results showed that collaborator reliability and cognitive accessibility had a significant effect on relevance, and 36% of the variance in relevance was explained by cognitive accessibility and reliability.

Moreover, this study is the first that examined the effect of network ties on physical accessibility for collaborator selection in the research universities context. Additionally, the proposed model can help IS researchers and servers as a starting point to develop additional theoretical models for expert finding systems in the university, such as supervisor selection model and paper reviewer model. These models should be integrated with current expert finding systems in universities.

Practically, this study provided several practical implications for expert finding system designers, research collaborators, researchers, and universities. For expert finding system designers, the research model can be integrated with current expert finding systems to improve their effectiveness concerning the selection of the appropriate collaborators. Recommendations concerning the combination of influential factors are also provided. The designers of expert finding systems mainly depend on the relevance between collaborator documents and user query; this model discovered that the relevance also depends on cognitive accessibility and reliability of collaborator. Additionally, this research model can help academic researchers by providing criteria about individuals with whom they can collaborate. Furthermore, the proposed model can motivate academic researchers to give feedback and rate a collaborato's competency levels after collaboration so that the retrieval process of expert finding systems is refined. Moreover, this model can motivate researchers to update and share expertise information to increase their selection opportunity by other researchers to participate in research collaboration. Finally, this research provides universities with criteria for research collaborator selection; these criteria will improve the process of collaborator selection and accordingly, research productivity in universities.

VIII. FUTURE RESEARCH

This research provides suggestions for future research.

First, this study tested 11 factors and categorised them into three dimensions (namely, human capital, social capital, and cultural capital) according to the STHC and SCT models. Further research can examine the influence of other factors on collaborator selection, for example, institution-related factors (e.g., geographical location and organisation size) and task-related factors (e.g., task importance, and criticality). Additionally, future researchers can identify new influential factors by interviewing collaborator seekers in universities. Moreover, upcoming researchers can extend the proposed model using other theories.

Second, as the target respondents of this study were academic researchers from research universities in Malaysia, further investigation is required to test the proposed model in different universities and research institutions in different countries. This would help in model generalisation and application of empirical findings in different contexts.

Third, this study provided recommendations to the designers of expert finding systems according to the validated model. They should incorporate this model with current expert finding systems in universities to improve the collaborator selection process.

Fourth, in the university context, researchers must develop a human-interaction model for other tasks, such as supervisor and reviewer selection. These models can be incorporated with current expert finding systems to improve their effectiveness.

Fifth, concerning Malaysian universities, expert finding systems are present in different universities, such as UTM and U; upcoming researchers can initiate IS research based on a theoretical foundation for expert retrieval systems in Malaysia, for example, developing user satisfaction and system success models for expert finding systems.

IX. LIMITATIONS OF THE STUDY

Despite the theoretical and practical contributions of this study, it suffered from some limitations highlighted in the following. First, the empirical data for this study were collected from research universities in Malaysia context, and the participants were the academic researchers who have experience in research collaboration. Therefore, the proposed model may not be generalized to other countries. Second, the proposed model was developed based on integrating two theoretical models. Though, the model may not cover all the influential factors on collaborator selection such as task criticality and institution size. Third, the research approach for this study was limited to quantitative and data collection was done using survey method. However, considering a mixed-method or a qualitative approach may lead to identifying new factors from researchers' viewpoint.

X. CONCLUSION

In the university context, expert finding systems help researchers by recommending suitable research collaborators automatically. These systems identify experts according to the content of their documents and ignore the human interaction perspective. Human interaction factors should be incorporated with current expert finding systems in the university context to improve their effectiveness in identifying suitable research collaborators. Human interaction factors include those that influence researchers' decision to collaborate with

TABLE 6. Measurement items.

Construct	Items	Mean	SD	Measuring items	Source
Relevance	RELV1	4.149	0.798	The collaborator's knowledge matches the field of knowledge whose expertise I need.	[62]
	RELV2	4.100	0.804	The collaborator is working on similar topics and/or areas.	[96]
	RELV3	4.112	0.788	The details in collaborator's published documents are related to my current topic interests.	[42]
	RELV4	4.123	0.741	The collaborator has broad knowledge related to the research collaboration task.	[92]
Reliability	RELIA1	4.109	0.794	The collaborator knows very much about the subject of research area of the needed knowledge	[62]
	RELIA2	4.072	0.793	The collaborator is an expert and has been working on this subject for at least 5 years.	[94]
	RELIA3	4.077	0.834	The information that I get from this collaborator is easy to comprehend	[92]
	RELIA4	4.106	0.872	The collaborator has a track record of dependability on similar research areas.	[95]
Physical accessibility	PHA1	4.089	0.837	The research collaborator's location is nearby.	[95, 153]
	PHA2	4.032	0.809	It is easy to make a face-to-face appointment with this collaborator.	[62, 154]
	PHA3	4.123	0.892	The collaborator responds to communications through phone, email and social media within acceptable duration of time	[62]
	PHA4	4.095	0.908	The collaborator is easily accessible through phone, email and social media.	[96]
Cognitive accessibility	COGA1	4.264	0.783	I can easily communicate with the collaborator	[94]
	COGA2	4.135	0.784	The collaborator is able to give me clear and concise answers	[96]
	COGA3	4.083	0.773	It is easy for me to process the explanations given by the collaborator.	[62, 92]
	COGA4	4.112	0.777	The knowledge contribution from the collaborator is easy to understand.	[42, 92]
	COGA5	4.026	0.777	The collaborator's suggestions can be easily implemented.	[42]
Relational accessibility	RELA1	4.401	0.633	The collaborator with whom I feel comfortable.	[62]
	RELA2	4.284	0.743	The collaborator who makes me feel relaxed when I want to ask him/her for task knowledge	[92]
	RELA3	4.272	0.755	The collaborator who never gives me the feeling of being a burden when asking a question	[96]
Network ties	NET1	4.032	0.834	I know this collaborator on a personal level	[83]
	NET2	4.000	0.876	I find it easy to interact with this collaborator to exchange information.	[60, 83, 155]
	NET3	3.971	0.869	I have frequent communication with this collaborator.	[60, 84]
	NET4	3.989	0.902	I can be flexible with this collaborator	[60]
Reputation	REP1	3.284	0.962	In my selection I will consider the collaborator's seniority level	[14]
	REP2	3.782	0.892	In my selection I will consider the collaborator's research reputation	[14, 75]
	REP3	3.384	0.943	In my selection I will consider reputation of the collaborator's home institution	[14, 156]
Commitment	COMM1	4.060	0.853	The collaborator provides all the necessary time to support and accomplish the goals of the collaboration.	[64]
	COMM2	4.086	0.807	The collaborator has a sense of belonging to the collaboration	[157, 158]
	COMM3	4.037	0.837	The collaborator gives priority to the collaboration.	[157]
Complementary skills	COMP1	3.960	0.789	I will choose a collaborator who can contribute complementary skills	[67, 75]
	COMP2	3.865	0.792	I need to find a wide range of complementary skills from my collaborator for use with my skills	[159]
	COMP3	3.905	0.833	Compared to my skills, complementary skills of collaborator are important.	[159]
	COMP4	4.074	0.805	We need each other's skills to accomplish the collaboration goals and responsibilities	[76]
Research experience	RESE1	3.874	0.837	The collaborator's number of years since the publication of the first scientific work.	[1, 146, 160]
	RESE2	3.923	0.855	The collaborator's number of years in supervisory roles.	[160]
	RESE3	3.951	0.819	The collaborator's number of years since his/her appointment in the university.	[160]
	RESE4	3.960	0.832	The collaborator's total number of publications.	[160, 161]
	RESE5	3.943	0.827	The collaborator's total number of collaboration projects.	[160, 161]
Cultural Experience	CULE1	3.625	0.895	Collaborator who has experience with colleagues of the same and different gender	[49]
	CULE2	3.599	0.895	Collaborator who has experience with colleagues of the same and different race	[49]
	CULE3	3.593	0.890	Collaborator who has experience with colleagues of the same and different nationalities	[49]
	CULE4	3.685	0.811	Collaborator who has experience with colleagues of the same and different academic disciplines	[49]
	CULE5	3.590	0.896	Collaborator who has experience with colleagues of the same and different socio-economic status	[49]
Collaborator Selection	COLS1	4.060	0.646	I have clear understanding of what collaborator selection is.	[162, 163]
	COLS2	4.029	0.706	It is important to have a process for selecting collaborators in my university.	[14, 75, 156]
	COLS3	4.106	0.662	It is necessary to have knowledge about how to select research collaborators.	[162, 163]

a particular research collaborator in real life. There is a dearth of studies that examine the factors influencing collaborator selection. This study examined human capital, social capital, and cultural capital factors that influence collaborator selection and how collaborator seeker prioritises the factors. It developed and validated a theoretical collaborator selection model for expert finding systems in research universities based on integrating the STHC model and the social capital theory.

Moreover, it examined the effect of collaborator reliability and cognitive accessibility on relevance. Furthermore, it provided guidelines for expert finding system designers to integrate the proposed collaborator selection model with current expert finding systems in universities. Empirical results indicated that the important factors that influence collaborator selection in the research universities context were cognitive accessibility, reliability, and relevance, commitment, physical accessibility, complementary skills, cultural experiences, and research experience.

Surprisingly, the results revealed that network ties, relational accessibility, and reputation were insignificant concerning collaborator selection. Moreover, mediation analysis showed that relevance and network ties have a significant mediating effect on collaborator selection. According to IPMA test results, cognitive accessibility, reliability, and relevance are the most important factors for collaborator selection. Theoretically, this study is one of the first studies that integrated the STHC model and social capital theory and proposed a research model for collaborator selection in the research universities context. It is among the initial studies that examined human capital, social capital, and cultural capital factors that influence collaborator selection in the university context. Moreover, it provides practical implications for expert finding system designers, researchers, collaborators, and universities.

APPENDIX A

See Table 6.

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