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Importance of social capital for knowledge acquisition– DeepLIFT learning from international development projects

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ABSTRACT

This paper aimed to examine the influence of internal and external social links within NGOs' international development project ecosystems on the knowledge acquisition process. The goal was to propose a model that enhances the gathering and transformation of missing knowledge, leading to more effective solutions for the complex developmental challenges faced by different NGOs. A dataset was gathered from 215 NGOs operating in the European Union and Western Balkans, involved in international development projects. Neural network models were employed to develop a prediction model that accurately distinguished between high and low levels of knowledge acquisition (with AUC values exceeding 0.8 for each model). Additionally, by utilizing advanced methodology, we uncovered valuable insights into the key factors contributing to an NGO's level of knowledge acquisition. These findings have significant implications for NGO international development efforts, growth, and performance. The predictive and interpretable mathematical models, based on neural networks, demonstrate the highest accuracy in identifying the social capital factors that most strongly influence organizations operating with varying levels of knowledge acquisition.

1. Introduction

Nonprofit, nongovernmental organizations (NGOs) are active within the global framework of dealing with emergencies after the state has decided not to act or is not in the position to act. NGOs back up international development (ID) efforts dealing with salient and frequently controversial challenges of great complexity. Their mission is to globally alleviate poverty, establish better governance and institutional capacities, as well as to bring forward vital issues on human rights and climate change (Ramalingam, 2013). However, policy makers find their accomplishments highly unsatisfactory, despite the auspicious fact of NGOs being able to operate independently and expansively. Pressure within and without has resulted in merely slight improvements for a huge number of beneficiaries (Banks et al., 2015; Banerjee et Duflo, 2011; Ika, 2012; Munk, 2013) who were left deprived of the desired impact over a period of 60 years, during which time trillions of dollars almost went to waste through international development projects (Easterly, 2006).

Aiming at viable solutions in global emergencies, NGOs need to sustain their organizational capacity and ability to secure resources relevant to their project goals. NGOs are currently socially and financially deficient, lacking relevant knowledge and support, and there is an additional stumbling block of striving to attend to the needs of the local population while at the same time following somewhat

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different donors' visions and goals (Briere et al., 2015). NGOs networks are big and dense but also heterogeneous and, therefore, challenging for the diversified cultural landscapes and contexts in which NGOs operate (Lee at al., 2016). NGOs projects are multi-stakeholder and cross sector, with solid social capital basis, which is considered an important precondition for society and its governments run more smoothly (Uslaner, 2000), but their stakeholder commitment, collaboration, alignment and adaptation seem too soft to unlock the missing resources located in their organizational repositories and network operations and thus secure the project success. Systemic and deep interactions among project stakeholders enhance a better alignment of their goals, interests and needs, resulting in a higher level of accountability, mutual trust and respect as well as more effective outcomes (Mikovic et al., 2020). Multidimensional features of social capital display a huge impact both in the case of crowdfunding fundraising (fundraising performance) and reaching donors (participation performance) (Ba et al., 2022).

However, NGOs should invest far more efforts towards creation and nurturing relations to leverage the missing project knowledge and thus reach their full potential accomplishing their missions and project goals providing solutions for people and societies in need. Keeping a balance between different focuses - how to perform a project, with whom and for whom- while embracing the social capital sitting in their project ecosystems, NGOs pave the way for acquisition of knowledge in the form of concrete and durable solutions for those in need.

1.1. Theoretic and conceptual framework of the research

Our research paper builds upon established knowledge management maturity models, incorporating aspects of social capital that impact knowledge acquisition in NGOs (Mikovic et al., 2020; Mikovic et al., 2019a; Mikovic et al., 2019b). Recognizing the lack of sensitivity in these models to an NGO's current level of knowledge acquisition, we aim to refine them to yield more precise outcomes. These improved models are intended to guide management in making informed decisions about investing in social capital features, based on the organization's awareness of knowledge acquisition. We anticipate that our findings will not only have practical value for international development entities but also contribute significantly to the theoretical understanding of social capital, knowledge management, and project management. This should enhance the operational stability of newer NGOs and those with limited social capital, leading to improved knowledge acquisition standards and, ultimately, better performance indicators for NGOs.

As presented in Fig. 1, the social capital embedded in project ecosystems of nongovernmental organizations is one of the relevant factors in building a successful model for effective and efficient predicting of the level of knowledge acquisition. **The main objective of our study** is to forecast and comprehend the relationship between social capital and the knowledge gained in nonprofit organizations, utilizing advancements in the explainability of machine learning models (Angelov et al., 2021; Linardatos et al., 2021). To achieve this, we have formulated **two distinct research questions**:

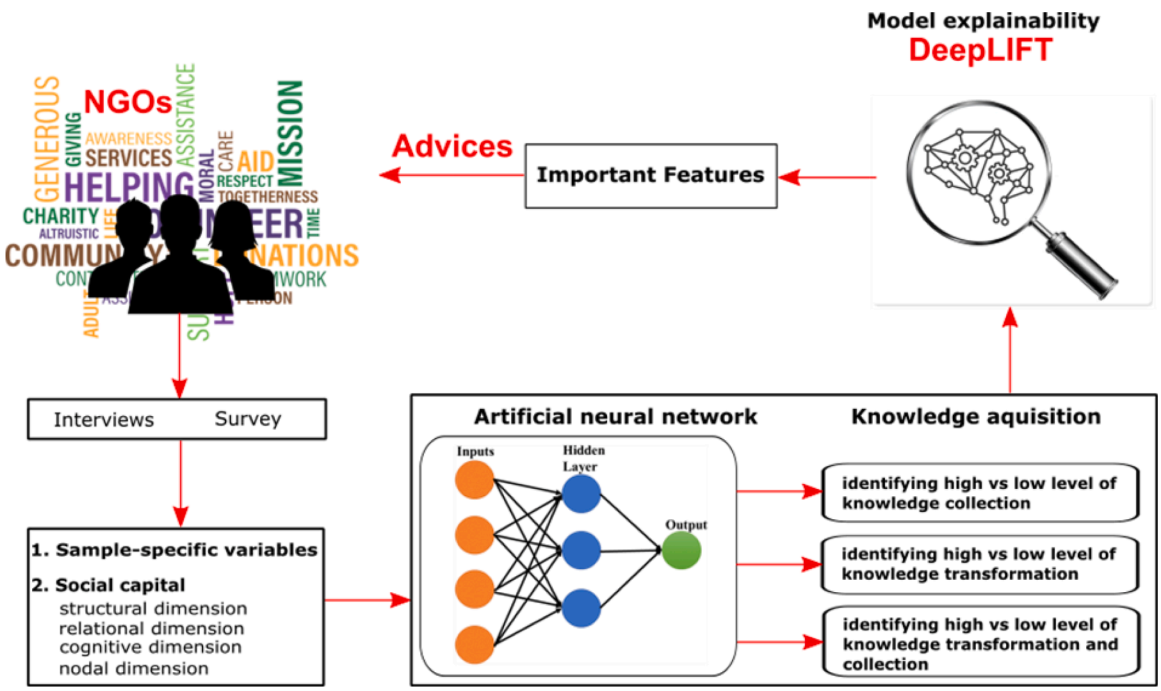


Fig. 1. Conceptual framework of the research. Surveys and interviews are conducted with an NGO, and information collected is categorized into informative social capital variables that are used by the proposed system to both estimate the level of knowledge acquisition and to extract highlights and lowlights of measured data thus providing the NGO the necessary insights into their knowledge acquisition performance and directions to improve it.

1. To evaluate which factors of social capital affect knowledge acquisition, distinguishing between high and low levels of both positive and negative impacts on organizations that function with varying degrees of knowledge acquisition **(Research Question 1**). It is vital for resource-constrained organizations to enhance the knowledge acquisition process through social capital embedded within their project ecosystems. NGOs, inherently limited in resources, are constantly seeking innovative solutions but often face shortages in finances, time, personnel, and know-how to support their development efforts and bridge existing gaps. Consequently, they must depend on their connections, networks, and individuals both within and outside their organizational boundaries.
2. To pinpoint the key mechanisms driving the collection and transformation of knowledge (**Research Question 2**). NGOs take pride in their diverse partnerships and recognize their varied benefits. However, they often struggle with effectively leveraging the social capital accessible to them for the purpose of gathering necessary knowledge and converting it into impactful outcomes, such as innovative solutions for those in need. This transformation of knowledge into practical impact is the ultimate aim NGOs strive for through their international development projects. Therefore, it is crucial to illuminate the dynamics of power and cooperation within these organizations.

2. Literature overview

2.1. Social capital

Social capital is defined as actual as well as prospective resources brought together and available through a network of individuals or social units via being built into or generated by it (Nahapiet et Ghoshal, 1998). There are two types of social units that we are about to address in this research paper: intraorganizational level of analysis and interorganizational level of analysis. Across various dimensions including social capital theories of weak ties (Granovetter, 1973), structural holes (Burt, 1992), social resources (Lin et al., 1981) and knowledge networks (Phelps et al., 2012), we examined structural (Burt, 2004), relational (Granovetter., 1992), cognitive (Tsai et Ghoshal, 1998) and nodal (Phelps et al., 2012), dimensions and elements of social capital. In our research, consistent with prior studies (Mikovic et al., 2019a, 2019b), we analyzed the structural dimension of social capital through general pattern of relations between participants, the presence or the absence of network ties between participants, type of ties that is open and closed ties, network position and structural equivalence (Burt, 2004). The relational dimension is scrutinized through the characteristics of the relations that develop over time through human interactions (Granovetter, 1992), including intensive and long-term communication, trust, closeness, reciprocity, norms and sanctions (Putnam, 1993) and obligations and expectations (Burt, 1992). The cognitive dimension pertains to the resources that foster shared representations, interpretations, and systems of meaning among network members (Cicourel, 1973), including shared narratives (Orr, 1990), common values, vision and goals (Tsai et Ghoshal, 1998). Lastly, the nodal dimension is defined through the characteristics of nodes, which can be individuals or collectives, acting as both recipients and sources of information and knowledge (Phelps et al., 2012) characterized by the diversity of network contacts (Perry-Smith, 2006), power (Rothaermel et Hess, 2007), the capacity to receive and transfer knowledge (Rothaermel et Alexandre, 2009), and the depth of knowledge (Tallman et Phene, 2007).

2.2. Knowledge management and knowledge acquisition

Knowledge management intrigues the scientific community for decades. It is about a complex concept, addressed by plenty of literature providing different definitions, approaches and models. Maier et Remus (2003) find that knowledge management is interpreted either through people-oriented or technology-oriented theories. For one group of authors (Karlsen et Gottschalk, 2004; Zhu, 2008), knowledge management is about the functions of the knowledge management lifecycle. For the other group of authors (Swan et al., 1999; Kotnour, 2000; Cope et al., 2006; Zang, 2007) it is about the value it creates for individuals and the entire organization. Overall, it is understood as the ability to leverage knowledge for the sake of successful achievement of goals set by an organization (Rubenstein-Montano et al., 2001). Organizations introduce knowledge management practices applying different stages that exist in the lifecycle of knowledge (Meyer et Zack,1996) including effort to manage it accordingly. According to the leading knowledge management scholars, there are the following accountable stages and elements of knowledge management: creation (or innovation); acquisition (or collection, transformation and accumulation); dissemination (or transfer); and usage (or application) (Bukowitz et Williams, 2000; McElroy, 2003; Wiig, 1993; Meyer et Zack,1996). The term 'knowledge management maturity' (Kulkarni et Louis, 2003) refers to the scope and level of consistent and effective usage and management of knowledge and its relevant stages including knowledge, organization and information technology as key prerequisites that influence an organization's knowledge management maturity.

In our study, we approach knowledge management by focusing on its two primary dimensions: enablers and processes (Santoro et al., 2018). Enablers are the mechanisms that aid in facilitating knowledge management activities among individuals, teams and organizations. These enablers promote the generation, sharing, and protection of knowledge, while also providing the necessary infrastructure to enhance knowledge processes. Conversely, knowledge management processes involve the organized coordination of managing knowledge effectively. This includes activities such as the creation, sharing, storage, and application of knowledge. Particularly in this paper, we emphasize social capital as a crucial enabler of the knowledge acquisition process. We explore its significant impact on the innovation capacities of NGOs and their overall performance, highlighting the vital role social capital plays in the effective management of knowledge within these organizations

Hamel (1991) defines knowledge acquisition as a process of knowledge management which consists of collecting knowledge from various sources such as documents and experts. Given the organizations are constrained with knowledge self-creation, there is a motivation to establish inter-organizational collaborations to identify, select and use external knowledge to benefit the organization. Once collected from different sources, transformed and codified up to the needs of the organization, it permits organizations to generate value, improve processes, products and services and, therefore, achieve competitive advantage. Acquiring knowledge is a key precondition of growth and innovation. The primary task of this knowledge management phase is to grasp relevant information so it can be successfully adapted and integrated, which will in turn allow formulation of concepts and questions, elucidate problems and make meaningful inferences (Mathew, 1985). Bosilj Vukšić et al. (2010) emphasize that during knowledge acquisition organizations tend to codify knowledge that is present in different shapes to create an added value (Chisholm, 1982). They further explain that it is important to reach the hidden knowledge of individuals and groups, its sequencing and structuring that is transforming its tacit form that was acquired through observation, practice and stories into a true, understanding and easily accessible form beneficial to the entire organization. To that end, socialization has been seen as a key leverage (Nonaka, 1994) as it enhances individual and group sharing nd transferring of knowledge.

In our paper, we align with the concept proposed by Dezi et al. (2021) that successful acquisition of knowledge hinges on an organization's understanding of knowledge management. Specifically, knowledge management serves as a critical intermediary between a firm's external embeddedness and its ability to be ambidextrous, which in turn leads to enhanced organizational performance. The value creation for an organization depends on intangible and knowledge-based resources which can be acquired externally or developed internally by employees and various departments.

2.3. Social capital and knowledge acquisition

Literature provides plenty of approaches towards social capital and knowledge acquisition. While we are focused on how internal and external social capital of NGOs influence knowledge acquisition, other research directions explored it's more specific processes which motivated our study. For instance, how personal social networks affect individual's life satisfaction, information overload, and well-being (Pang, 2022, 2019), deepening understanding the impact of new media on personal networks. Additional insights were uncovered by showing how knowledge is shared, perceived, and utilized in societal and political contexts, which is crucial for effective knowledge management strategies (Pang et Liu, 2023), addressing issues like social network exhaustion, privacy invasion, and the effects of network characteristics on psychological outcomes.

In our paper, relying on previous similar studies (Mikovic et al., 2020, 2019a: Mikovic et al., 2019b), we analyze knowledge acquisition with the assumption that it can be positively influenced by the organizational and project social capital. When acquiring the lacking knowledge, it is expected that NGOs would try to access either internal (considering individuals, teams, or the organizational knowledge repository) or external sources (i.e. partner organizations, experts, etc.) who may provide the knowledge in question. The model proposed by Mikovic et al. (2020) points to the intra-relational and inter-nodal dimensions of social capital in that regard. The process of knowledge acquisition and its successfulness largely depend on quality of ties and good rapport among employees, as well as teams. Also, prior knowledge depth as well as capacity of NGOs to receive and transfer the project knowledge seems equally important for knowledge acquisition as well. NGOs often nurture internal links, relations and communication as prescribed by their organizational policies, culture and employee rulebooks but more should be invested to explore the project opportunities to promote teamwork, team cohesion, team leadership, team decision-making and similar practices that would soften the relations and unlock the trust, respect, giving and sharing.

These findings are in line with Papa et al. (2020) who suggest that firms can develop competitive advantages through both knowledge exploitation and exploration within and outside the firm's boundaries. It is about the knowledge acquisition capacity, known also as inbound open innovation, that helps firms develop new combinations of knowledge enriching the pool of solutions available to solve innovation challenges endemic to the firm. Moreover, firms that pursue widely and extensively inbound open innovation are more likely to obtain more knowledge and technologies capabilities (Santoro et al., 2018). The inbound open innovation mechanism describes the acquisition of external knowledge or technologies through practices such as licensing-in or participating in communities, while the outbound open innovation mechanism explains the transferring of internal knowledge or technologies to external actors for economic or strategic purposes (Cheng et Shiu, 2015).

2.4. Applications and explainability of machine learning models in social science

DeepLIFT can be used as a powerful method for interpreting the predictions of deep learning models in the field of social science and knowledge management. Its applications can range from understanding the dynamics of social networks to analyzing the flow of knowledge within organizations. For instance, DeepLIFT can be used to explore the factors that contribute to the formation and maintenance of social ties in a given network.

The study of Joshi et al. (2023) showcases a novel approach to detect misinformation in social media platforms using explainable AI techniques. Specifically, the authors leverage a DANN model as a black box to predict the target labels, and then apply an explainable LIME-based method to interpret these predictions locally. This approach enhances the model's interpretability, trustworthiness, and applicability in real-world settings. In the study of Duddu et Boutet (2022) model explanations are used to determine the importance of different input attributes for a model's prediction. However, such explanations can inadvertently reveal sensitive information. The authors also proposed a novel approach to perform attribute inference attacks on model explanations and compare the results with two types of attribute-based explanation algorithms: backpropagation-based explanations (IntegratedGradients and DeepLift) and perturbation-based explanations (GradientSHAP and SmoothGrad). Our research also reveals that DeepLift can be been employed to investigate the impact of social capital on knowledge sharing among employees within an organization. By providing a way to attribute the importance of input features to the output of a deep learning model, DeepLIFT helps researchers gain insights into the underlying mechanisms that govern social interactions and knowledge transfer. As such, it has the potential to contribute to a better understanding of how social networks and knowledge management systems operate in the real world, ultimately leading to more effective policies and practices in these areas. Overall, DeepLIFT is a powerful and versatile method that can provide insights into the inner workings of deep learning models across a wide range of applications in different fields, including computer vision, natural language processing, and bioinformatics, among other.

DeepLIFT and SHAP (Shapley Additive Explanations) (Lundberg et Lee, 2017; Lundberg et al., 2018) are both techniques used to explain the predictions of machine learning models, particularly neural networks. However, they have different approaches to feature attribution and can yield different results in certain scenarios. For example, DeepLIFT primarily provides a local explanation for a specific prediction, while SHAP offers a more global explanation that considers the contributions of each feature across all possible combinations of feature values. While DeepLIFT is based on gradients, SHAP is model-agnostic, meaning it can be applied to any machine learning model, not just neural networks. In this work, we used both approaches, to see how big the matches are in the results and if we can really trust the results obtained.

3. Methodology used

In the field of predictive modeling, traditional methods like Logistic Regression and Decision Trees have typically been trusted for their simplicity and ease of understanding when it comes to unraveling intricate connections in datasets. Nevertheless, there are situations where these established models might not fully grasp complex patterns and produce the best outcomes. This is the reason why in our research, we used predictive modeling methodology with robust focus on ANN (artificial neural networks), DeepLIFT and SHAP methods. We examined 215 nonprofit, nongovernmental organizations (NGOs) registered in the European Union (EU) and Western Balkans (WB) that implement international and local development projects. To collect and verify the data collected, we used different data collection methods (content analysis, survey, and interviews) to triangulate the data collected and deepen our understanding of findings but also reduce the bias collection of data may be prone to.

We used three types of variables: sample specific (related to scope, location and management), input (related to internal and external social capital features that is structural - number, strength, type and diversity of ties/contacts, network structure; relational - trust, respect, reciprocity, obligations and expectations; cognitive - norms, vision, goals, values, narrative, and nodal - power, depth of knowledge, capacity to receive and transfer knowledge) and outcome (related to knowledge acquisition features such as collection of missing knowledge and transformation of tacit/experiential into explicit/concrete knowledge). The tested input and output variables are a result of synthesis of the existing literature we elaborated in the literature overview section. We applied deductive reasoning, we wanted to draw conclusions by going from general information to specific findings. All aspects of external/internal social capital and knowledge acquisition NGOs evaluated, with their abbreviations used later in results section, are presented in Table 1 below.

After having collected the data, in order to find accurate knowledge acquisition levels and understand what social capital factors led to those levels, we employed the predictive modeling methodology that is ANN (artificial neural networks) method as a key classification tool and DeepLIFT method as a key interpreting and explanatory tool.

Table 1
Descriptive data for external and internal social capital and knowledge acquisition.

Social capital dimensions and elements		Knowledge acquisition
External	Internal	
S1 Number of ties (network openness)	**woS1** Number of ties (openness)	**KA1** Collection of missing knowledge
S2 Number of direct ties (network closeness)	**woS2** Number of direct ties (closeness)	**KA2** Knowledge collection mechanisms
S4 Network position (central)	**woR1a** Strength of ties (intensity)	**KA3** Transformation of tacit into explicit knowledge
S5 Structural equivalency	**woR1b** Strength of ties (duration)	**KA4** Knowledge transformation mechanisms
R1a Strength of ties (intensity)	**woR2** Closeness of employees	
R1b Strength of ties (duration)	**woR3a** Trust (towards individuals)	
R2 Closeness of actors	**woR3b** Trust (towards teams)	
R3 Trust	**woR3c** Trust (towards organization)	
R4 Respect	**woR4** Respect (mutual)	
R5 Reciprocity	**woR5a** Reciprocity (individuals)	
R6 Norms (and respect of norms)	**woR5b** Reciprocity (teams)	
R7 Obligations and expectations	**woR6a** Norms (and respect of norms)	
K1 Common vision and goals	**woR6b** Sanctions	
K3 Common values	**woR7a** Obligations and expectations (individuals)	
K5 Common narrative	**woR7b** Obligations and expectations (teams)	
N1 Diversity of network contacts	**woK1** Common vision and goals	
N2a Power (resources)	**woK3** Common values	
N2b Power (results)	**woK5** Common narrative	
N2c Power (influence)	**woN2a** Power (resources)	
N3 Capacity to receive and transfer knowledge	**woN2b** Power (results)	
N4 Depth of knowledge	**woN2c** Power (influence)	
	woN3 Capacity to receive and transfer knowledge	
	woN4 Depth of knowledge	

3.1. Sample description

The findings of this research address new research questions of predicting and understanding the underlying connects of knowledge acquired in nonprofits, while it builds on previous work of estimating their knowledge maturity and impact (Mikovic et al., 2020, 2019a, 2019b). We conduct our analyses on data gathered across the three years period on the role of social capital in nonprofit organizations with regards to knowledge management and organizational processes.

Our sample comprises 215 surveyed nonprofit organizations that are civil society-based and operate in the European Union (EU) and Western Balkans (WB). These organizations implement international development and cooperation projects aimed at improving the quality of life for marginalized groups. The surveyed organizations include 28 EU national platforms that bring together around 2000 EU NGOs (CONCORD, 2017), 47 international networks that consist of approximately 2000 EU NGOs (Social Platform, 2017), and 1000 WB NGOs actively involved in international cooperation and development (Sterland et Rizova, 2010). Our data stratified sample comprises of 215 NGOs with fully completed questionnaire (out of 5000 NGO that were reached out to). Given acquired sample size and targeting the confidence level of 95 % with ß-0.80 (probability of type I error 0.05 and study strength 0.80), the confidence interval is measured at 6.5 % from the ideal 4 % that would be achieved with the sample size of 300.

We selected NGOs from these two regions to assess the extent to which contextual and developmental differences may influence the phenomena we examined. The EU region is economically and socially developed, with internationally experienced, resourceful, and networked NGOs. On the other hand, the WB region faces challenges such as slow and inconsistent democratic reform, corruption, unemployment, and a fragile peace, and has relatively weaker (local) NGOs working for a European perspective and social justice. This sampling approach makes our findings valuable not only for NGOs operating in the EU and WB regions but also for NGOs working globally in both more and less developed contexts. In terms of location of operation, 60 % of the surveyed NGOs are based in the EU (out of which a majority come from Belgium – 11, followed by Greece – 8, Croatia – 8, Germany – 7, Italy – 7, etc.) while 40 % are in WB (Serbia, Montenegro, North Macedonia, Albania, Bosnia and Herzegovina).

The surveyed NGOs include both young and mature, as well as large and small organizations. The youngest organization surveyed was only 1 year old, while the oldest was 98 years old. Most of the organizations fall between 10 and 20 years old. In terms of financial capacities, the surveyed NGOs implement both small- and large-scale projects, which are reflected in their annual turnover. Locally based organizations are more likely to run small-scale projects (5–10 per year) and grants (up to 100,000 euro), while international organizations operate with large-scale projects (over 20 per year) worth millions of euros. The surveyed NGOs also vary in terms of the number of people involved in the work of the organization and the type of engagement. Bulk of the surveyed NGOs also work in international development and cooperation (20.5 %), and in most cases they come from the EU. Other surveyed NGOs define themselves as being engaged either in local development (16.7 %) or in culture, media and education (9.3 %), environment and wellness (12.1 %), philanthropy and humanitarian aid (9.8 %), social services (19.1 %) and civil society and voluntarism (12.6 %).

3.2. Dataset description

To identify the key drivers of knowledge acquisition in NGOs, a series of statistical analyses were conducted. The first step was to check the internal consistency of all the social capital (SC) and knowledge acquisition (KA) variables examined. For external social capital, a scale of 21 questions demonstrated a satisfactory level of internal consistency with a Cronbach alpha of α=0.815, split-half

Table 2
Social capital of the organization – descriptive data for interorganizational level.

	Social capital dimensions and elements	Mean	Std. Dev.	Kurtosis	Skewness	Kolm-Smir.
S1	Number of ties (network openness)	4.24	.890	2.452	−1.460	.258*
S2	Number of direct ties (network closeness)	4.20	.696	4.151	−1.291	.310*
S4	Network position (central)	3.57	.929	−0.418	−0.425	.277*
S5	Structural equivalency	3.22	.955	−0.555	−0.266	.229
R1a	Strength of ties (intensity)	3.74	.830	.761	−0.866	.349*
R1b	Strength of ties (duration)	4.20	.736	4.469	−1.463	.312*
R2	Closeness of actors	3.45	1.017	−0.247	−0.566	.233
R3	Trust	4.13	.657	.867	−0.542	.309*
R4	Respect	4.43	.607	.202	−0.689	.314*
R5	Reciprocity	4.24	.766	.575	−0.884	.298*
R6	Norms (and respect of norms)	4.46	.594	.310	−0.725	.325*
R7	Obligations and expectations	3.68	.908	−0.184	−0.464	.269*
N1	Diversity of network contacts	3.55	.734	.651	−0.493	.293*
N2c	Power (influence)	3.47	1.049	−0.408	−0.557	.281*
N3	Capacity to receive and transfer knowledge	3.99	.730	.891	−0.568	.296*
N4	Depth of knowledge	3.74	.890	.487	−0.628	.326*
N2a	Power (resources)	3.83	.898	2.181	−1.294	.353*
N2b	Power (results)	3.94	.780	1.605	−0.908	.326*
K1	Common vision and goals	3.83	.809	.211	−0.488	.284*
K3	Common values	3.82	.688	.284	−0.364	.327*
K5	Common narrative	3.60	.790	.775	−0.649	.303*

**<0.01; *<0.05.

(Spearman-Brown coefficient) reliability at 0.816, and an average item correlation with the overall score of $r = 0.58$. For internal social capital, a 23-question scale also demonstrated a satisfactory level of internal consistency with a Cronbach alpha of α=0.925, split-half (Spearman-Brown coefficient) reliability at 0.883, and an average correlation of items with the overall score of $r = 0.59$. The knowledge acquisition scale consisted of 4 questions (two quantitative and two qualitative) and showed a high level of internal consistency with a Cronbach alpha of α=0.916, split-half (Spearman-Brown coefficient) reliability at 0.842, and an average correlation of items with the overall score of $r = 0.61$. The surveyed NGOs evaluated their external, internal social capital, and knowledge acquisition, as specified in Tables 2–4.

The skewness values indicate that some of the variables are not normally distributed, with negative values indicating a longer left tail and positive values indicating a longer right tail. For example, the variables related to network openness (S1) and network closeness (S2) have negative skewness values, suggesting that there may be a larger proportion of individuals with fewer ties in the network. In contrast, the variable related to power through influence (N2c) has a negative skewness value, indicating that there may be a larger proportion of individuals with less influence. The kurtosis values indicate whether the distribution is more or less peaked than a normal distribution. For example, the variable related to network openness (S1) has a kurtosis value of 2.452, indicating a very peaked distribution. In contrast, the variable related to network position (S4) has a kurtosis value of −0.418, indicating a relatively flat distribution. Similar interpretation could be done for other two tables. The dataset is described in more detail in our previous papers (Mikovic et al., 2020, Mikovic et al. 2019a, Mikovic et al., 2019b).

3.3. Artificial neural networks as a classification tool

In the realm of predictive modeling, conventional techniques such as Logistic Regression and Decision Trees have traditionally been relied upon as interpretable and intuitive tools for understanding complex relationships within datasets. However, in certain instances, these conventional models may fall short in capturing intricate patterns and delivering optimal results. In our study, we encountered a scenario where these traditional methodologies failed to provide satisfactory predictive accuracy, highlighting their limitations in handling intricate and non-linear data dependencies. To address this challenge, we turned to neural networks, a class of machine learning models often regarded as "black box" due to their complexity and inscrutability. While their inner workings can be challenging to interpret, neural networks excel in capturing intricate patterns and relationships within data, making them a compelling choice when transparency takes a back seat to predictive performance. In this paper, we explore the application of neural networks as a powerful alternative to traditional models, emphasizing their ability to uncover complex associations that may remain elusive to more interpretable approaches.

The data classification process endeavors to anticipate the category to which an observation belongs for each observation in a population. Prediction of multiple classes simultaneously (multi-classification framework) was successfully applied in the study of Mikovic et al. (2019b) with the task of predicting knowledge management maturity of NGOs. In the study, the model was trained to predict knowledge management maturity level decomposed into several factors simultaneously, where the decomposition consisted of eight variables, each with five levels. With the high accuracy obtained in the study, the approach had a drawback in not being able to highlight the levels of importance of each variable on the output, thus limiting knowledge discovery of the study. This was the major challenge since the models could not provide concrete information which levels of knowledge management to improve via the most

Table 3
Social capital of the organization – descriptive data for intraorganizational level.

	Social capital dimensions and elements	Mean	Std. Dev.	Kurtosis	Skewness	Kolm-Smir.
R1a	Strength of ties (intensity)	4.20	.831	2.227	−1.317	.291*
R1b	Strength of ties (duration)	4.01	.925	−0.298	−0.708	.252*
R2	Closeness of employees	3.68	.943	.370	−0.643	.259*
R3a	Trust (towards individuals)	4.38	.706	2.595	−1.259	.293*
R3b	Trust (towards teams)	4.27	.726	−0.023	−0.694	.264*
R3c	Trust (towards organization)	4.34	.671	.221	−0.711	.280*
R4	Respect (mutual)	4.38	.685	.677	−0.910	.298*
R5a	Reciprocity (individuals)	4.41	.670	1.508	−1.091	.307*
R5b	Reciprocity (teams)	4.31	.676	.999	−0.829	.266*
R6a	Norms (and respect of norms)	4.07	.713	2.693	−0.968	.314*
R6b	Sanctions	3.08	1.135	−0.905	.211	.192
R7a	Obligations and expectations (individuals)	3.90	.862	.553	−0.739	.289*
R7b	Obligations and expectations (teams)	3.89	.828	1.010	−0.847	.319*
S1	Number of ties (openness)	4.17	.719	.166	−0.574	.257*
S2	Number of direct ties (closeness)	4.18	.676	2.356	−0.877	.299*
K1	Common vision and goals	4.13	.783	.541	−0.714	.246*
K3	Common values	4.31	.809	2.404	−1.375	.277*
K5	Common narrative	3.87	.812	.110	−0.594	.310*
N2a	Respect (resources)	3.97	.773	.987	−0.749	.310*
N2b	Power (results)	4.08	.796	2.446	−1.152	.307*
N2c	Power (influence)	3.81	.855	.516	−0.718	.307*
N3	Capacity to receive and transfer knowledge	4.11	.744	.196	−0.587	.271*
N4	Depth of knowledge	3.87	.727	1.140	−0.672	.332*

**<0.01; *<0.05.

Table 4
Knowledge acquisition of the organization – descriptive data for key KA features.

		Mean	Std. Dev.	Kurtosis	Skewness	Kolm-Smir.
KA1	Collection of missing knowledge	3.84	.765	.344	−0.409	.287*
KA3	Transformation of tacit into explicit knowledge	3.73	.934	−0.186	−0.571	.285*

**<,01; *<,05.

influential social capital factors. That is why we decided to explore additional techniques to unlock capabilities of peering into the black-box and understand how the model works. Moreover, the complexity the multi-class classification introduces in modeling approaches, even though it benefits the accuracy, makes drawing insights and conclusions from such models very difficult and empirically unstable. With this trade-off in mind, a single task, binary classification approach is the approach adopted in this study. For each binary output variable representing a level of knowledge acquisition, a separate explainability model was learned, and state-of-the art techniques in decomposing the importance of factors considered (Shrikumar et al., 2017) are then used to extract useful knowledge from the data. The method of explainability that is utilized involves employing backpropagation (Goodfellow et al., 2016) to compare the activation of each neuron to a predetermined "reference activation," ultimately recording and assigning a contribution score based on the differences in the neurons. Essentially, it is a way of digging back into the feature selection inside of a highly non-linear algorithm.

3.3.1. Data transformation

Three different models for binary classification tasks were developed separately depending on a variable used as output: 1) Knowledge Acquisition 1 (KA1 – related to knowledge collection), 2) Knowledge Acquisition 3 (KA3 – related to knowledge transformation) and 3) the sum of KA1 and KA3 variables. Knowledge collection mechanisms (KA2) and knowledge transformation mechanisms (KA4) were treated as supporting qualitative info and as such were separately analyzed, presented (see Table 9) and discussed. When the variables KA1 and KA3 are used as the model output, the variable was transformed into a binary variable where the value is set to 0 if the current value is less than or equal to 3, otherwise the value is set to 1. A similar procedure was performed for the new cumulative output feature obtained by addition of two variables, KA1 and KA3, but in this case the threshold for variable binarization was set to 6.

3.3.2. Artificial neural networks for binary classification task

Due to highly non-linear relations between inputs and outputs, artificial neural networks (ANNs) are selected as a method of choice in our work guided by prior arts in the field (Garson, 1998). Artificial neural networks (ANNs) are composed of multiple layers of artificial neurons or nodes, including an input layer, one or more hidden layers, and an output layer. These nodes are connected to adjacent layers and have specific weights and a threshold-based activation function. If a node's output is higher than the threshold value, the node becomes activated, allowing data to flow into the next layer of the network. Otherwise, a node is deactivated and no data is passed along to the next layer of the network. These kinds of architectures are capable of producing highly non-linear functions that can capture underlying processes in the data accurately. Because the optimization of artificial neural networks (ANNs) is non-convex in nature, the most suitable architecture and parameters, including the number of hidden layers, the number of neurons, and appropriate activation functions, are determined using a grid-search approach. The number or layers and neurons will change during the network grid search process until satisfactory ANN performance is achieved. However, typically using a small number of hidden layers (such as using a single hidden layer) is often advisable to avoid instability in the training process caused by local minima in non-convex optimization (Rai et al., 2005). The final layer in ANNs is used for producing scores of classes, where the sigmoid and softmax activation functions are typically used for binary and multi classification tasks, respectively. However, ANNs are typically regarded as "black-box" models as it is difficult to understand the exact relationship between the input and output data. Recent advances in the field, though, show that it is possible to effectively and accurately extract these relationships and thus additional knowledge from the data (Ribeiro et al., 2016; Shrikumar et al., 2017). One of these techniques, DeepLIFT, is exploited in this paper for demystifying neural network as a black-box model. In order to optimize a model for binary classification tasks, 'our approach used binary cross-entropy or focal- loss functions. Bearing in mind that the classes are imbalanced, a weighted binary cross-entropy loss function was used, where weights are determined as the reciprocal of all class appearances in the dataset.

In our experiments we found that the network with satisfactory performance and stable training consists of a single hidden layer with 50 neurons, each using ReLU activation function. To minimize the aforementioned loss function, the Adam optimizer is used, with

Table 5
Parameters and training process for each model.

	Hidden layers	Epochs	Loss function	Loss function parameters
KA1	[50]	100	Focal-loss	α=0.8, γ=2, Adam(lr=0.001)
KA3	[50, 30, 10]	200	Binary Crossentropy	class_weights, Adam(lr=0.001)
KA1 + KA3	[50]	100	Binary Crossentropy	class_weights, Adam(lr=0.001)

the initial learning rate set to 0.001. All models are trained with batch size 4 and 100 or 200 epochs. We attempted to combine other activation functions for hidden neurons and learning parameters in the multilayer perceptron (MLP), but the statistical performance was either similar or worse than the previous results. Parameters and training process for each model are provided in Table 5. The available dataset was split into five folds by using data stratification technique (Botev et Ridder, 2017). During cross-validation, the folds are constructed in a way that maintains the proportion of samples for each class. The main objective of this process is to assess the model's capacity to make predictions for novel data that were not used to train it, thereby providing insight into the model's generalization ability and potential overfitting issues. In the results section, we present the outcomes obtained from five independent cross-validation experiments, where the performance measures of accuracy, precision, recall, and AUC are summarized.

3.4. DeepLIFT as an interpretability and explainability tool

As it was mentioned before, it is challenging to extrapolate the exact relationship between the input and output data in the black-box models such as artificial neural networks. Because of non-linear relations between inputs and output, increasing models' complexity and losing model explainability was an expected step. The whole idea behind interpretable and explainable ML is to avoid the black-box effect we get, for example by using neural networks, thus becoming essential in solutions we build nowadays.

DeepLIFT, short for Deep Learning Important Features, is a technique that involves backpropagating the contributions of all neurons in an ANN to each feature of a specific input, with the goal of decomposing the output prediction. This process allows for the calculation of an importance ranking of input features. This method measures the activation of each neuron against its corresponding "reference activation" and computes contribution scores based on the resulting difference. In this way, the method can explain the difference in output from some 'reference' output in terms of the difference of the input from some 'reference' input. For each ANN model we developed three different output values. DeepLIFT method was run in order to demystify feature importance. To determine the reference activation for DeepLift method, it is necessary to choose a reference input for each neuron in the network. The reference input can be a fixed value, zero or some other value depending on the application. It is worth noting that the choice of reference input can affect the interpretation of the results, so it is important to choose a reference input that is appropriate for the application and the specific task at hand. In this case, we used a data of several NGOs for reference input and output, because one of the authors works within the international development NGO sector for more than two decades and knows exactly how much the marks are valid for certain NGOs she cooperates with. According to the DeepLIFT creators one should consider using multiple different references to interpret a single input (NGO) and averaging the results over all the different references. Here we have used five different NGOs as references considering their diversity and location. Moreover, we received confirmation of our choice later in the results, because those connections were already empirically confirmed in the literature.

The obtained results are presented below, the model features influence the knowledge acquisition process inside NGOs, as well as the related references that confirm the derived conclusions. The results obtained after the DeepLIFT method has been applied on each ANN model we developed are presented in Tables 6, in the section with results. The algorithm was also run separately for both classes of outputs, negative and positive (0/1). The collective DeepLIFT values can show how much each predictor contributes, either positively or negatively, to the target variable.

For the purpose of better understanding of the next chapter of our paper, where we present and discuss the findings, we would like briefly to share how the values provided by the DeepLIFT are interpreted. The most influential positive features are the ones that push the prediction higher than the reference value (this value is calculated for each feature independently), these features will have a positive impact on NGOs knowledge acquisition process (the higher the value the more likely the positive outcome). On the other hand, the least influential features are those whose score is the smallest as compared to the reference value and they are unlikely to influence the objective of knowledge acquisition inside an NGO. To disentangle reverse-proportional relationships between features and the objective, we analyze the positive and negative class of our objective independently and report most and least influential features for each. Taking into consideration that the developed models achieved a high accuracy, potential improvements in specific areas of social capital could lead to benefits in the NGOs sectors where they can encourage certain process and become more effective

4. Results and discussion

Our goal was to assess what social capital factors influence knowledge acquisition discriminating high level from low level of

Table 6
The results of the binary classification task for the logistic regression (LR), decision tree (DT) and neural network (NN) models.

Model	Precision	Recall	F1-score	Accuracy	ROC AUC
LR KA1	0.235	0.251	0.243	0.233	0.268
LR KA3	0.210	0.214	0.212	0.244	0.255
LR KA1 + KA3	0.180	0.174	0.179	0.211	0.224
DT KA1	0.766	0.698	0.730	0.722	0.788
DT KA3	0.667	0.744	0.708	0.545	0.591
DT KA1 + KA3	0.544	0.521	0.533	0.666	0.688
NN KA1	0.982	0.844	0.906	0.851	0.912
NN KA3	0.909	0.723	0.785	0.851	0.878
NN KA1 + KA3	0.777	0.853	0.809	0.798	0.845

Table 7
The positive and negative class of the objective are analyzed independently, and top most and least influential features for both are reported and cross-referenced with the existing literature.

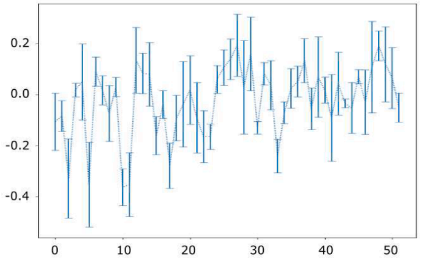
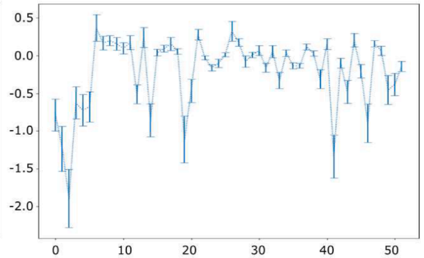
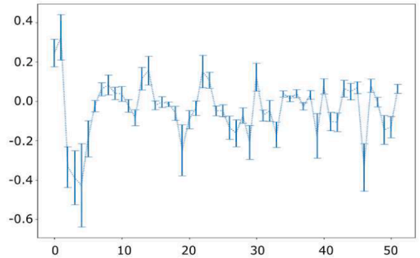
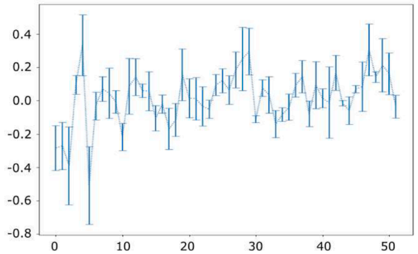
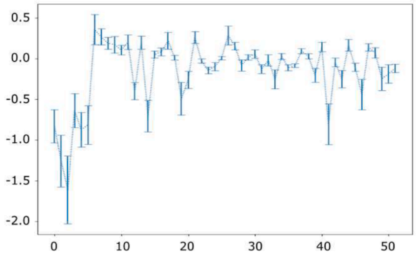
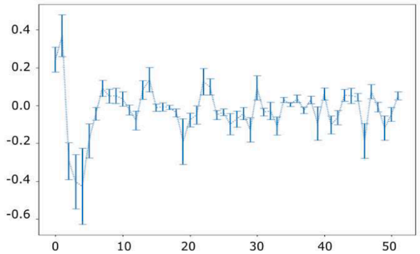
Knowledge Acquisition 1 – Collection of missing knowledge Social Capital	Knowledge Acquisition 3 – Transformation of tacit knowledge into explicit knowledge Social Capital	Knowledge Acquisition 1 + 3 – Cumulative
NEGATIVE CLASS (Class 0)		
		
Top positive features: [N3, woN2b, woS1, N2c, R1a] DL scores: [0.19, 0.19, 0.16, 0.14, 0.13] Top negative features: [A2, A3, Scope_16, Scope_8, R5] DL scores: [−0.36, −0.35, −0.35, −0.33, −0.28]	Top positive features: [Location, N2c, K3, R1b, woK1] DL scores: [0.37, 0.32, 0.28, 0.24, 0.21] Top negative features: [Scope_8, woR6b, Scope_7, R7, woK5] DL scores: [−1.90, −1.33, −1.24, −1.11, −0.90]	Top positive features: [Scope_7, Scope_4, R2, K5, woS2] DL scores: [0.32, 0.25, 0.16, 0.15,0.12] Top negative features: [Scope_14, Scope_10, woK5, Scope_8, R7] DL scores: [−0.43, −0.39, −0.34, −0.33, −0.25]
POSITIVE CLASS (Class 1)		
		
Top positive features: [Scope_14, woN2a, woS1, N4, woN2c] DL scores: [0.33, 0.31, 0.30, 0.25, 0.21] Top negative features: [Scope_16, Scope_8, Scope_4, Scope_7, A2] DL scores: [−0.51, −0.39, −0.28, −0.27, −0.22]	Top positive features: [Location, N2c, Position_2, K3, R5] DL scores: [0.36, 0.29, 0.27, 0.26, 0.22] Top negative features: [Scope_8, Scope_7, Scope_14, Scope_4, Scope_16] DL scores: [−1.61, −1.26, −0.87, −0.83, −0.81]	Top positive features: [Scope_7, Scope_4, R2, K5, N1] DL scores: [0.37, 0.24, 0.17, 0.13, 0.10] Top negative features: [Scope_14, Scope_10, Scope_8, R7, woK5] DL scores: [−0.43, −0.40, −0.29, −0.19, −0.19]

Table 8
The most and least influences of social capital on low and high level of knowledge acquisition – detailed presentation of results.

Top ZERO positive = SC factors that *most influence* the LOW level of KA 1
[N3, woN2b, woS1, N2c, R1a]

Internal SC	woN2b – Power (achieved results) woS1 – Number of ties (network openness)
External SC	N3 – Capacity for receiving/transferring knowledge N2c – Power (level of influence) R1a – Strength of ties (intensity of communication)

Top ZERO negative = SC factors that *least influence* the LOW level of KA 1
[A2, A3, Scope16, Scope8, R5]

Internal SC	-
External SC	A2 – Active contacts with nonprofit sector A3 – Active contacts with business sector R5 – Reciprocity
Ind Var	Scope8 – Local development Scope16 – Civil society and volunteerism

Top ONE positive = SC factors that *most influence* the HIGH level of KA 1
[Scope14, woN2a, woS1, N4, woN2c]

Internal SC	woN2a – Power (achieved results) woN2c - Power (material/immaterial resources) woS1 – Number of ties (network openness)
External SC	N4 – Depth of knowledge
Ind Var	Scope14 – Social services and vulnerable groups

Top ONE negative = SC factors that *least influence* the HIGH level of KA 1
[A2, Scope4, Scope7, Scope8, Scope16]

Internal SC	-
External SC	A2 – Active contacts with nonprofit sector
Ind Var	Scope4 – Environment and health Scope7 – International development and co Scope8 – Local development Scope16 – Civil society and volunteerism

Top ZERO positive = SC factors that *most influence* the LOW level of KA 3
[Location, N2c, K3, R1b, woK1]

Internal SC	woK1 – Common vision and goals
External SC	N2c - Power (level of influence) K3 – Common organizational values R1b - Strength of ties (longevity of ties)
Ind Var	Location – geographic position

Top ZERO negative = SC factors that *least influence* the LOW level of KA 3
[Scope8, Scope7, woR6b, R7, woK5]

Internal SC	woR6b – Sanctions woK5 – Common narrative
External SC	R7 – Obligations and expectations
Ind Var	Scope7 – International development and coop. Scope8 – Local development

Top ONE positive = SC factors that *most influence* the HIGH level of KA 3
[Location, Position2, N2c, K3, R5]

Internal SC	-
External SC	N2c - Power (level of influence) K3 – Common organizational values R5 – Reciprocity
Ind Var	Location – Geographic position Position2 – Middle level management

Top ONE negative = SC factors that *least influence* the HIGH level of KA 3
[Scope4, Scope7, Scope8, Scope14, Scope16]

Internal SC	-
External SC	-
Ind Var	Scope4 – Environment and health Scope7 – International development and co Scope8 – Local development Scope14 – Social services and vulnerable g. Scope16 – Civil society and volunteerism

Top ZERO positive = SC factors that *most influence* the LOW level of KA 1+3 cumulative
[Scope 7, Scope 4, R2, K5, woS2]

Internal SC	woS2 - Number of direct ties (network closeness)
External SC	R2 – Closeness of actors K5 – Common narrative
Ind Var	Scope7 – International development and cooperation Scope4 – Environment and health

Top ZERO negative = SC factors that *least influence* the LOW level of KA 1+3 cumulative
[Scope14, Scope10, woK5, Scope8, R7]

Internal SC	woK5 – Common narrative
External SC	R7 – Obligations and expectations
Ind Var	Scope8 – Local development Scope10 – Philanthropy and humanitarian work Scope14 – Social services and vulnerable groups

Top ONE positive = SC factors that *most influence* the HIGH level of KA 1+3 cumulative
[Scope 7, Scope 4, R2, K5, N1]

Internal SC	-
External SC	R2 – Closeness of actors K5 – Common narrative N1 - Diversity of network contacts
Ind Var	Scope7 – International development and coop. Scope4 – Environment and health

Top ONE negative = SC factors that *least influence* the HIGH level of KA 1+3 cumulative
[Scope8, Scope10, Scope14, R7, woK5]

Internal SC	woK5 – Common narrative
External SC	R7 – Obligations and expectations
Ind Var	Scope8 – Local development Scope10 – Philanthropy and humanitarian work Scope14 – Social services and vulnerable groups

influences against organizations which operate with lower or higher knowledge acquisition (Research Question 1), as well as identify the mechanisms that are key drivers of knowledge collection and transformation (Research Question 2).

In regard to the RQ1, we managed to allocate the most and the least influencing factors against organizations which operate with lower or higher knowledge acquisition. Table 6 shows the results of single task binary classification when using logistic regression, decision tree algorithm and the appropriate neural networks, we described earlier (see Table 5 with the parameters for each model), for each output separately. A recommended setting from Table 5 has obtained the best performance across all metrics, obtaining high accuracy and area under ROC curve (AUC) values that are task-specific and may be used with higher confidence for estimation whether future knowledge acquisition will be high or low. As already announced, for this dataset and related task higher precision is shown by neural networks (see Table 6).

Our findings are in line with the majority of already known theoretical standpoints. However, our research goes one step further allocating in detail and with the highest accuracy the most and the least influencing social capital facets against organizations which operate with lower or higher knowledge acquisition. Table 7 below provides the results obtained by using DeepLIFT approach, for each model separately. We analyze the negative and positive class of our objective independently and report the most and the least influential features for each. In figures, which are part of the table, the 95 % confidence intervals of DeepLIFT scores, for each feature, are presented. For the inference phase of the models, the execution time is quite short, with predictions typically taking less than a second. On the other hand, the DeepLift algorithm can take up to a maximum of 10 min.

The same results are also presented in Table 8 below, but from different point of view. Table 8 is a narrative interpretation of data, scores and features codified in Table 7, created primarily for the audience less acquainted with ANN and DeepLIFT methodology, with aim to ease their understanding of the results obtained. To avoid confusion with the combination of, for example, positive class and positive features, in some places the negative class is called ZERO, and the positive class is called ONE.

In addition to our investigation involving DeepLIFT, we also incorporated the SHAP (Shapley Additive Explanations) (Lundberg et Lee, 2017; Lundberg et al., 2018) model into our analytical framework. The inclusion of SHAP was aimed at enhancing our understanding of feature importance and model interpretability and to compare the results obtained using both methods. SHAP provides valuable insights into the contributions of individual features towards model predictions, shedding light on the black-box nature of complex neural networks. The SHAP methodology was chosen, because in comparing the DeeLIFT and SHAP methodologies, there are notable differences in their respective approaches to feature attribution and interpretability. While DeepLIFT focuses on attributing contributions to input features for a specific prediction, SHAP employs a more holistic approach by considering feature contributions

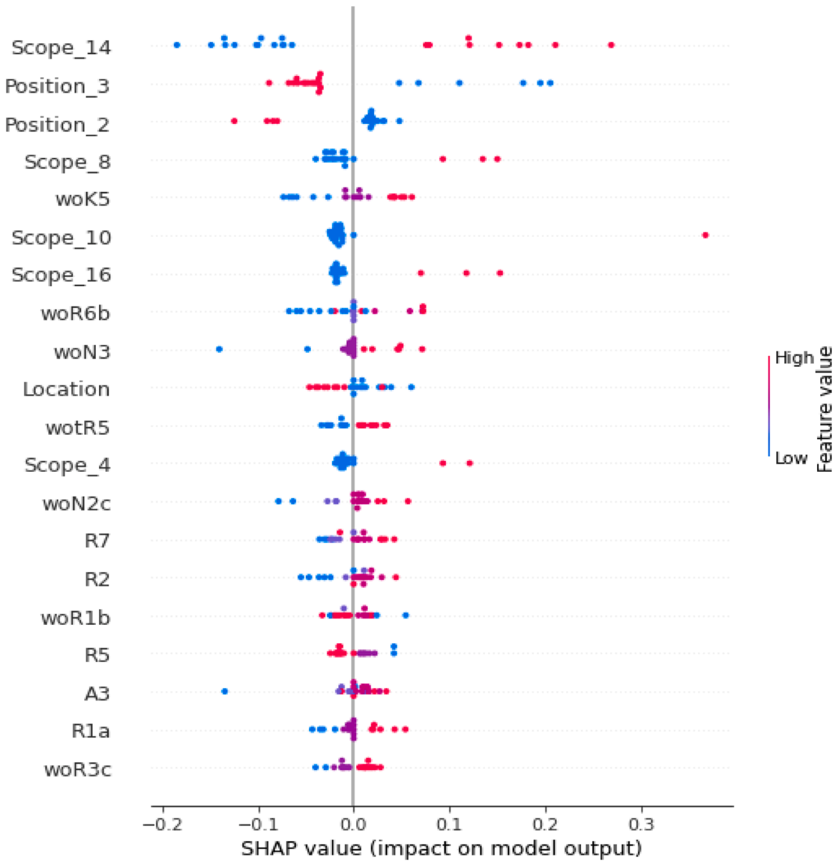


Fig. 2. SHAP values. Directionality impact of the features for the model KA3.

across all possible permutations of feature values. This distinction in methodology led to nuanced disparities in our interpretation of feature importance and model behavior, which was the goal, i.e. to check if there is and how much overlap there is in the results obtained.

Here, we focused our attention primarily on the KA3 model, a more complex neural network architecture we used, compared to KA1 and KA1 + KA3 models which are simple. The reason for this selective presentation is twofold: First, KA3 is a multiplex process and far more challenging to manage than KA1. KA3 model's complexity allows it to capture intricate data relationships that simpler models struggle to discern, making it the most promising candidate for our research objectives. Second, presenting detailed results for all models could potentially inundate the paper, compromising readability and clarity. It is essential to note that the results and conclusions obtained for the KA3 model closely align with those of other models explored in our study. The results obtained using the SHAP approach and a comparison with the results obtained using DeepLIFT are presented below.

Our findings reveal that both DeepLIFT and SHAP offer valuable insights into model interpretability, each with its unique strengths and considerations. The choice between these methods may depend on the specific research question, the level of interpretability required, and the nature of the dataset. What we got is that although the approaches were completely different, the results and the selected features and their importance in the neural network matched to a large extent.

In terms of whether different results can be expected for feature selection, this is contingent upon the data and the specific use case. The focus of DeepLIFT is primarily on explaining individual predictions, and how particular features were influential in determining a specific outcome can be highlighted by it. On the other hand, a more comprehensive view of feature importance across all predictions can be provided by SHAP, and consistent patterns in feature importance can be identified. Whether different results are anticipated is dependent on factors such as the nature of the data, the complexity of the model, and the specific research question being addressed. In practice, it is often deemed valuable to utilize both DeepLIFT and SHAP (or similar techniques) to attain a more complete understanding of how predictions are generated by the model and which features are deemed most influential.

In Fig. 2, the x-axis represents SHAP values, while the y-axis encompasses all the features for model KA3. Every data point on the chart corresponds to a specific SHAP value associated with a prediction and feature pair. The color scheme employed here is indicative of feature magnitudes: red denotes higher feature values, whereas blue signifies lower ones. By examining the distribution of these red and blue data points, we can gain valuable insights into the overall impact and directional influence of the features.

Based on the dispersion and interval of SHAP values, it can be seen to what extent and in what way certain variables affect the final outcome of the prediction, more precisely the level of KA3 output. In the chart above, some of the following insights could be concluded: Higher value of Scope_14 leads to higher level of KA3. Lower value of Scope_14 leads to lower level of KA3. The same holds for Scope_4, Scope_8, and Scope_16. It could be noticed that the most influential variables are compatible with those presented in Table 7, such as Scope_4, Scope_8, Scope_14, Scope_16, Location, woN2c, woR6b, and woK5, which confirms the previously obtained results. For the DeepLIFT, we have shown five of the most influential variables, rather than all variables.

Following the above said, and as presented in Tables 7-8, we find that NGOs whose knowledge acquisition is lower:

- Internally, rely most on their internal achievements, their personal direct and indirect contacts when collecting the missing knowledge, and on their vision, mission and goals when transforming tacit (experiential) into explicit (concrete) knowledge.
- Externally, rely most on the capacity of their network members to receive and transfer knowledge, influence the knowledge processes and manage intensive communication between network members when collecting the missing knowledge, and on network values, shared narrative, history of cooperation and influencing capacities when transforming tacit into explicit knowledge.
- Internally and externally, rely least on sanctions, contacts within the sector, obligations and expectations, reciprocity, and individual narratives when collecting the missing knowledge and transforming tacit (experiential) into explicit (concrete). This is particularly visible with NGOs that implement international and local development projects, that are predominantly inclined to philanthropy and humanitarian work, social services and vulnerable groups.

On the other hand, NGOs whose knowledge acquisition is higher:

- Internally, rely most on their internal achievements, their personal direct and indirect contacts but also available internal resources when collecting the missing knowledge.
- Externally, rely most on the capacity of their network members to receive and transfer knowledge when collecting the missing knowledge, and on their network influencing power, values, shared narrative, but also close cooperation and diversified contacts when transforming tacit into explicit knowledge.
- Internally and externally, rely least on individual narratives, contacts within the sector, and obligations and expectations when collecting the missing knowledge and transforming tacit into explicit. In general, the type of their activity is least associated with the knowledge acquisition process.

Common for NGOs that operate both with high or low levels of knowledge acquisition is that they recognize sanctions, obligations and expectations as the least stimulative knowledge acquisition features. Also, for some NGOs their geographic position and type of their activity do influence the collection of missing knowledge and the transformation process. Namely, NGOs which operate in international development and cooperation, and environment and health seem to be more responsive to the knowledge acquisition process.

A couple of features have been spotted that may explain the difference between the low and high level of knowledge acquisition in

NGOs. Namely, NGOs with higher levels of knowledge acquisition recognize middle level management staff as important leverage for knowledge transformation as well as reciprocal sharing between network members, access to diversified network contacts and to organizational resources. In other words, people who work on middle level management, most often in the capacity of project managers and/or coordinators, have been recognized as knowledge brokers internally bridging the knowledge between the top management and lower management staff but also enticing collection and transformation out of the organization borders. Also, access to resources through cross sector and multi stakeholder cooperation may fill the knowledge gap especially when there is a need for a specific and rare knowledge and skills and its transformation from individual, experimental and experiential into social or group and directly accessible to all people in the organization.

Important message for NGOs and generally all organizations who do recognize the importance of knowledge acquisition process, is that investment into middle management staff is worth the development of people who work as assistants, coordinators, or managers. Though, it is very challenging from the perspective of retainment philosophy as these people are most prone to job changes (due to temporary nature of projects). However, if the organization invests into people development, is consistent with its values, goals, narrative and secure sufficient resources (time, expertise, knowledge) internally and through its influential network and /or ecosystem respecting the culture of reciprocity and trust, this should raise expectations and the raise the motivation bar of all sides (staff, partners, associates, beneficiaries) important for knowledge acquisition process.

In regard to the RQ2, we have found out the mechanisms that are key drivers of knowledge collection and transformation, as presented in Table 9.

NGOs collect the missing knowledge most of the time through trainings, conferences, and consultations with experts and partners. These are already well known and quite traditional channels which through organizations try to learn, exchange and transfer. What does seem worrying is the very small percentage of NGOs who recognize consultations with beneficiaries as an important mechanism for learning about their needs to which NGO projects should provide meaningful solutions. This fact may explain the palliative rather than transformative effects of NGO work, the reason why developmental issues still remain wicked with complex contexts hardly influenced by NGOs as they rather opt to work for their beneficiaries instead with them. Also, mentoring and internships or job shadowing still have not been recognized as one of the most useful learning methods, massively advocated by the professional and scientific community in recent years. Learning by doing or on job learning and intensive mentoring and coaching from more experienced professionals are the golden standard for most of the top world companies today. Although NGOs could claim lack of financial resources as a key limitation factor for those incentives, it is still something reachable because the project ecosystems in which NGOs operate can provide that resource. NGOs do have plenty of opportunities in that regard, it is just the matter of recognizing it is needed first of all.

NGOs do transform tacit knowledge into explicit and in most of the cases they use manuals, minutes and their databases as key repositories for storage of written data, information, knowledge about certain processes, systems, rules, etc. Still, our analysis suggests that only small number of NGOs actually do that, which means that the majority of experiences, observations, experiments, practical knowledge and skills remain with individuals instead of being transferred and integrated into the organizational systems, processes and repositories. Thus, institutional memory of the organization remains cut from a chance to generate specific knowledge in the form of its intellectual capital, creating an added value to the organizational performance and impact.

4.1. Theoretical and practical implications

Our findings are theoretically both supportive and novel. Social capital researches have been present in the scientific community for more than five decades. The early theories proposed by Putnam, Granovetter and Burt have seen extensive application in a myriad of contemporary applied researches. There has been an increasing focus on the intricate correlations between social capital and knowledge management across various world regions, sectors, and methodologies, especially those utilizing recent advancements in machine learning and digital technologies. For example, AI models in finance provide early warnings for investors, big data analytics enhances innovation with a focus on individuals' roles. AI contributes to understanding knowledge sharing, emphasizing specific enablers and connections within organizations, all contribute to the premise that recent technological advances in machine learning play a vital role in human interaction and networking (Zhang et al., 2022; Lozada et al., 2023; Ghobadi et D'Ambra, 2013; Ghobadi,

Table 9
The most common used mechanisms for knowledge acquisition.

Knowledge collection	%	Knowledge transformation	%
Trainings	62,3	Manual	42,3
Consultations with experts	56,0	Minutes	40,9
Meetings	51,2	Database	39,5
Consultations with partners	41,5	Written procedures	36,1
Conferences	39,5	Publications/articles	8,8
Consultations with beneficiaries	12,1	Nothing offered	8,4
Mentoring	14,5	Patent	1,9
Online consulting (social networks)	8,4		
Internships	7,4		
Reporting	5,1		
Formal specializations	4,2		

2015; Zia, 2020; Meng et al., 2021; Tucakovic et Bojic, 2021). However, our research fills a notable gap in the existing literature. There is a dearth of research specifically targeting the unique social and knowledge acquisition processes in the international development sector and nonprofit organizations. Our paper makes a significant contribution in this area by revealing the potential impacts of machine learning concepts on knowledge management processes. We do this through an examination of the structural, cognitive, relational, and nodal features of social capital embedded in organizations and their internal and external project ecosystems. This novel approach offers valuable insights into the dynamics of knowledge acquisition and management in the context of the nonprofit sector, a domain that has been relatively unexplored in this light.

Practical implications of our work are versatile and may serve project managers, chief executive officers, human resource development managers, and policy makers. Our paper provides a guide how to use computer-based judgment in a way to enhance NGO international development efforts, growth, and performance. This is a very novel approach as so far very few papers used AI methods to dig social capital drivers influencing knowledge management process, out of which none used DL method to assess influences specifically related to knowledge acquisition in international development and cooperation sector which serves the higher societal causes.

From a managerial point of view, NGOs can utilize network analysis tools to map and evaluate their social networks, focusing on multi-stakeholder cooperation and middle management, as highlighted in our study. This includes examining partnership diversity, identifying key network players, and analyzing information flow. Such analysis helps NGOs strengthen weak ties, create new partnerships, and position middle managers as central figures in these networks, enhancing knowledge acquisition and dissemination. It emerges that NGOs adopting an active open approach to knowledge acquisition, are more likely to develop innovation capacity. Openness is recognized as a strong enabler of innovativeness and can increase the likelihood of creating internal capacities. In particular, an open approach fosters knowledge acquisition, creation, absorption, and connection, which in turn enhance the efficiency of an organization's open innovation strategy. This confirms the importance of expanding organization boundaries and suggests that it may offer several opportunities in discovering new contexts and exploring new knowledge. One possible explanation for NGOs is that engaging with project partners of varying nature (type, sector, context, region) can generate new ideas, since and organization can thereby access different knowledge bases. In turn, the high diffusion of new knowledge should at least challenge the open-mindedness inside the organization. This should start from the top management and consider the role of open projects ecosystems for innovation. Another managerial implication is that the development of knowledge managements process is likely to generate an open environment, presenting new opportunities of knowledge acquisition and transformation. In fact, internal and external organizational knowledge acquisition results from the capacity to share, combine and create new knowledge in the current dynamic environment NGOs operate in. Collaboration and knowledge exchange among internal departments are the starting point, while creating interactive spaces with external project partners where participants can share information and knowledge through common platforms should outgrow into a regular effort. Technology solutions via AI models provided alone are necessary for this to happen, but not sufficient to increase innovativeness. NGOs have to strengthen their propensity to collaborate by selecting the right project partner and adjusting the intensity of the relationships.

Human resources development (HRD) managers play a vital role in approaching knowledge acquisition. This underlines the importance of employee and human aspects in managing internal and external sources of knowledge as antecedents of innovation. In particular, HRD managers must promote initiatives to stimulate a collaborative approach to innovation, along with specific (learning) practices that can be useful to improve innovation. In the specific case of our paper, stimulating active learning behavior (via innovative learning methods such as mentorship, coaching, on-job-learning, job shadowing, knowledge hubs, etc.) would enable knowledge exploitation and exploration beneficial for developing organizational capabilities to generate innovation. Active learning processes of each individual can create a variety of knowledge within the organization, followed by innovation based on a combination of that knowledge. Next to it, a more concrete approach to empowering middle managers as key connectors of internal and external networks could ensure effective information flow and integration. Investing in middle manager mentoring and coaching for better communication and coordination ensures efficient integration and utilization of knowledge. Equipping middle managers with effective cross-sector communication, strategic networking, and collaborative project management skills would boost the NGO's knowledge acquisition and management capabilities, leading to more efficient and effective project implementation.

For policy makers, governments could utilize our findings to craft policies promoting multi and cross sector stakeholder cooperation. Policies might incentivize cross-sector collaborations with academic, business, and NGO partners, and enhance middle management skills in NGOs to boost NGO effectiveness in societal development and knowledge acquisition. Seeking external knowledge extensively and from heterogeneous sources (multistakeholder and cross sector policy and project partners) leads to many opportunities but also leads to a higher level of complexity. Policy makers can manage the allocation of attention between internal and external sources by cultivating a portfolio of different initiatives linked to the policies. This is even more evident in dynamic and turbulent development sectors and regions, which call for flexibility, external ideas and technologies and, therefore, a higher focus on development issues raised. Therefore, decisions about openness are essential for achieving positive societal changes. The multidimensional relationship built among different development state and non-state actors create an open knowledge system in which information and knowledge circulate through technological systems, creating internal capacities. These capacities, in turn, enhance the innovativeness required to respond quickly to the external dynamic needs, and nurture the conditions for accurate selection of external sources and partners.

5. Conclusion

Our paper concerns social capital, collection and transformation of missing knowledge of nonprofit, nongovernmental organizations from the European Union and the Western Balkans, who implement international development projects. Our goal is the assessment of the social capital embedded in their project ecosystems on knowledge acquisition of NGOs immersed in a variety of complex circumstances as well as reaching a model conducive to their most effective, optimized collaboration and integration.

The model we propose is a mathematical model based on neural networks' deep lifting process that can show with high accuracy what social capital factors influence most the knowledge acquisition level no matter where an NGO comes from, whether it has more or less employees, runs more or less projects, etc. Similar results were obtained using two approaches, DeepLIFT and SHAP, which additionally confirms the strength of the obtained results and enables us to interpret the results with greater certainty. Our cutting-edge research based on neural network approach tends to use social capital of nonprofit organizations for the purpose of examining and modelling the knowledge management acquisition. It confirmed that social capital influences knowledge acquisition process, which is something already known from the literature. However, this research in addition allocated with highest accuracy the most and the least influencing factors against organizations which operate with lower or higher knowledge acquisition. These findings provide data-driven confirmation to the NGO management that networking does bring added value if it is clear where to invest more and/or less when working with the project ecosystems. The knowledge acquisition process for NGO ecosystems of multiple stakeholders and cross sector convergence is greatly influenced by social links and thus requires a suitable model for the knowledge acquisition process to be successfully ingrained through social resources. This will prompt a higher standard in NGOs supporting and providing for the vulnerable layers of population, as well as unfolding sustainable solutions towards their progress.

This research paper, however, is restricted in a very similar way as some previous ones [Mikovic et al., 2020, Mikovic et al., 2019a, Mikovic et al., 2019b), the first restriction being that it only addresses a specific type of nonprofit, nongovernmental organizations with specific goals, values and missions. It only covers the territory of Europe, thus having impact only through NGOs in the EU and WB, whereas only implicitly affecting the nonprofit sector in all other regions. Finally, although there seems to be no significant relation between social capital and the heterogeneous structure of NGOs in terms of demographics, future studies could benefit from that kind of expanded research as well.

CRediT authorship contribution statement

Radmila Miković: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. **Branko Arsić:** Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Đorđe Gligorijević:** Conceptualization, Supervision, Validation, Writing – review & editing.

Data Availability

Data will be made available on request.

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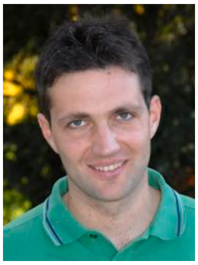

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