UNIVERSITÉ DE MONTRÉAL

AGENT-BASED MODEL OF FAB LAB COMMUNITIES

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RÉSUMÉ

Étant donné que les concepts d'innovation socio-technologique ont accéléré à la direction de la personnalisation massive, la fabrication par des laboratoires "Fab Lab" sera le prochain domaine intéressant à trouver son chemin vers la personnalisation dans un contexte collaboratif. Elle a été reconnue comme la prochaine révolution industrielle (Morel & Le Roux, 2016; Troxler, 2013), puisqu'elle peut soutenir de nouvelles innovations technologiques collaboratives en autorisant des individus à utiliser leurs ressources locales et de trouver leurs solutions économiques pratiques (Gershenfeld, 2006; Morel, Dupont, & Lhoste, 2015). Ce nouveau concept de collaboration communautaire peut être utilisé dans différents segments de service fournissant, c'est-à-dire des fins éducatives, des solutions de production, des pratiques personnelles, etc. Pourtant, il n'y a pas assez d'études pratiques pour aider le processus de choisir les stratégies les plus appropriées et des méthodes pour développer des interactions personnelles par les types différents de communautés Fab Lab. En conséquence, une simulation à base d'agent semble être un outil utile pour soutenir la conception des Fab Labs comme le futur modèle répandu pour les processus d'innovation, de fabrication ou d'apprentissage des compétences. Cette étude propose un modèle à base d'agent qui a été simulé en utilisant la plateforme AnyLogic et a été développé par un codage Java supplémentaire. En tenant compte de divers facteurs, il a été évalué par certaines techniques de vérification et de validation. De plus, deux séries d'expériences ont été menées pour soutenir la validité de ce modèle puisqu'il n'y a pas de données empiriques ni de variantes historiques disponibles pour comparer et vérifier les résultats de cette simulation avec une communauté Fab Lab réelle. En plus, d'autres expériences ont été menées afin d'étudier l'impact du seuil de déclenchement et l'intensité des programmes de motivation sur les interactions des membres de la communauté. Les résultats ont découvert des influences indéniables des programmes de motivation avec différentes configurations sur des communautés Fab Lab en termes de durée de la vie active, niveau de fait d'être actif, la compétence/ la connaissance transférée. Néanmoins, l'application des résultats dans certaines situations réelles peut révéler les contraintes cachées réelles pour améliorer ce modèle.

ABSTRACT

Considering that socio-technological innovation concepts have been accelerating in the direction of mass customization, fabrication through labs "Fab Lab" is going to be the next interesting domain to find its way toward customization in a collaborative context. It has been recognized as the next industrial revolution (Morel & Le Roux, 2016; Troxler, 2013) since it can support new collaborative technological innovations by empowering individuals to use their local resources and to find their practical economic solutions (Gershenfeld, 2006; Morel et al., 2015). This new concept of community-based collaboration can be used in different service providing segments, i.e. educational purposes, production solutions, personal practices, etc. Yet, there are not enough practical studies to assist the process of choosing the most appropriate strategies and methods to develop personal interactions through different types of Fab Lab communities. Accordingly, an agent-based simulation seems to be a useful tool to support the design of Fab Labs as the future widespread model for innovation, fabrication, or skill learning processes. This study proposes an agent-based model that was simulated using the AnyLogic platform and was developed by supplementary Java coding. In consideration of diverse factors, it was evaluated by some verification and validation techniques. Moreover, two series of experiments were carried out to support the validity of this model since there is neither related empirical data nor historical variants available to compare and check the results of this simulation with a real Fab Lab community. Besides, other experiments were conducted in order to study the impact of the triggering threshold and the intensity of motivation programs on interactions of the community members. The results uncovered undeniable influences of motivation programs with different setups on Fab Lab communities in terms of active lifespan, level of activeness, transferred skill/ knowledge. Nevertheless, applying the results in some real situations can reveal the actual concealed constrains to improve this model.

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LIST OF SYMBOLS, ABBREVIATIONS, AND VARIABLES

DIY	Do it yourself
DIWO	Do it with others
CoP	Community of Practice
3D	Three-dimensional
2D	Two-dimensional
MIS	Management Information System
MKIS	Marketing Information System
CRM	Customer Relationship Management
R&D	Research and Development
H-factor	Homophily factor
B	Beginner (skill level)
L	Learner (skill level)
P	Practicing (skill level)
M	Master (skill level)
MCA	Minimum collective agreement
$n \in N$	Set of Fab Lab members;
$m \in M$	Set of skill items;
S_{nm}^{t}	Level of skill *m* for member *n* at time *t*;
X_{nm}	Learning expectation of member *n* for skill *m*;
E_n	Extroversion level of member *n*;
Minvert	Minimum required extroversion difference for a proper communication;
Maxvert	Maximum acceptable extroversion difference for a proper communication;
ΔE_{ij}	Difference between extroversion levels of two agents *i* and *j (similarity factor)*;

Y_n	Technology talent of each member;
D_n	Diligence of each member (represents how serious a member is to pursue his goals);
F_m	Easiness of the skill item *m*;
I_n	Interest level of member *n* to participate in Fab Lab activities;
t_{nm}	Cumulated time that member *n* interacted for skill *m;*
T	Simulation horizon;
ΔT	Simulation time period in which we calculate t_{nm};
V	Steepness of Logistic S curve;
Mid_{nm}	Midpoint of S curve for member *n* and skill *m*;
Hf_n^t	The mean difference between all expectation levels and actual skill levels of agent *n* at time *t*;
Ae_{ij}^t	Attraction evaluation is the mean difference between all skill levels of agent *j* and all expectation levels of agent *i* at time t;
Coi_{ij}^t	Connectivity intensity between agent *i* and agent *j* at time *t*;
Vpt_n	Vector of *potential* connections for agent *n* in terms of skill and expectation levels;
Vps_n	Vector of *possible* connections for agent *n* in terms of extroversion levels;
Vfc_n	Vector of final connections for agent *n*;
P	Set of groups;
p	Group of agents in which agents may interact;
$\bar{p}$	Number of members in p;
SI_{nm}^t	Interest of agent *n* to interact over skill item m at time t;
CI_{pm}^t	Collective interest of group members in p towards skill item m at time t;
MCA_{pm}	Minimum collective agreement of p to interact for skill item m;
$l \in L_p$	Set of skills that p considers as *collaborative activities*;

$\overline{L_p}$ Number of skills that p considers as *collaborative activities*;

$h \in H_p$ Set of skills that p considers as *cooperative activities*;

$\overline{H_p}$ Number of skills that p considers as *cooperative activities*;

β_{pm} Collective expectation of group members in p for skill m;

α_{L_p} Average expectation of group members in p for *collaborative activities* (L_p);

α_{H_p} Average expectation of group members in p for *cooperative activities* (H_p);

$Vptp_n$ Vector of interacted skills by agent *n* through its *peer-to-peer* connections;

$Vptp_{nm}$ Element of vector $Vptp_n$ to show whether or not agent *n* interacted on skill *m*;

$Fgti_n$ Vector of interacted skills by agent *n* through its *group-to-individual* connections;

$Fgti_{nm}$ Element of vector $Fgti_n$ to show whether or not agent *n* interacted on skill *m*;

$Vgti_n$ Set of desired skills that agent *n* is interested to interact through *group-to-individual* connections;

$Vgti_{nm}$ Element of vector $Vgti_n$ to show whether or not agent *n* is interested to interact on skill *m*;

$Agti_p^n$ Set of available skills for agent *n* by group *p* as a *group-to-individual* interaction;

$Agti_{pm}^n$ Element of vector $Agti_p^n$ to show whether or not agent *n* is interested to interact with group *p* on skill *m*;

$\overline{Agti_p^n}$ Number of available skills offered by group *p* to agent *n* for a *group-to-individual* connection;

Ca Communication accessibility;

Tmp Threshold to start motivation programs;

Imp Intensity of the motivation programs;

Ei Increment of interest that can be increased by each motivation program;

Cps^t Community passiveness percentage at time *t*;

Cac^t	Community activeness percentage at time *t*;
θ	Lifespan of the Fab Lab community;
Aac	level of activeness of the community;
B_n	Indicator that shows whether agent *n* is passive or not;
A_n	Indicator that shows whether agent *n* is active or not;
Tts^t	Total transferred skill of the community during time *t*;
Ats	Average transferred skill of the community during its lifespan θ;
Inv_n^t	Status of agent *n* at time *t* that shows whether it works individually in Fab Lab or not;
Pin^t	Percentage of community population that are involved individually at time t;
Ain	Active population that is involved individually during the community lifespan;
Grp_n^t	Group working status of agent *n* at time *t;*
Pgr^t	Percentage of population that interact in groups at time *t;*
Agr	Active population that is involved in group activities during the community lifespan;
Nmt^t	Number of members who are motivated by motivation program at time *t*;
$Mcost$	Cost of motivation programs;

CHAPTER 1 INTRODUCTION

Classical marketing concepts propose distinct principles about the innovation process involved in new product development (Armstrong & Kotler, 2011c). What Fab Lab defines as a revolutionary idea is the productive combination of independency, digital technology, and community, which result in a pure agile system. This innovation and production concept introduces how to produce individually or do it yourself (DIY) while being supported by communities, which is introduced as do it with others (DIWO) (Morel & Le Roux, 2016). Companies reasonably look for their real customers and their needs. They always assess the received ideas in terms of profit or loss, which may directly lead them to success or failure in the market competitions (De Wit & Meyer, 2010), whereas Fab Labs respond to personal requirements through open innovation. Fab Lab can differently offer a variety of simple original designs with a drastic reduction in production costs. It is a form of democratization in fabrication (Blikstein, 2013; Morel & Le Roux, 2016).

1.1 Main distinction

In comparison with other current DIY programs, the main point of differentiation of Fab Labs is the benefit from the knowledge and technological advices provided by community members in a multidisciplinary environment. The collaborative setting of Fab Labs allows their members to learn new skills, to share their practices, to explore the fabrication methods, and to gain technological experience. Consequently, the role of communities is highlighted as a competitive sustainable advantage to pioneer community-based production models. Yet, to achieve a precise comprehensive model, two main problematic issues including the nature of these communities and the interactions within them need more consideration.

1.2 Challenges

Building a community as one of the basic components of the Fab Lab concept is the most challenging phase because there is a considerable difference between community and market, while both of them can represent a group of consumers (Krieger & Müller, 2003). One of the similar efforts, which is developed in commercial organizations to support the problem solving process, is communities of practice (CoPs) (Wenger, Etienne et al., 2002; Wenger, Etienne & Snyder, 2000). The informal structure with no hierarchy interconnection of CoPs makes them the most similar system to Fab Lab communities in terms of framework and characteristics although their general purposes are different (Flechet, 2016). As a result, the community approach and general model of CoPs can be used and adapted in Fab Lab communities. In addition, personal decision-making patterns in terms of thoughts, emotions, and behaviour respecting the individuals' interests should be clearly determined as the agent's attribute during the modeling.

Another critical challenge in the development of a Fab Lab simulation is the modeling of the flow of knowledge and skills through learning, sharing, and their dissemination process, which emerge from community interactions. There are several efforts to model knowledge sharing within and among organizations based on SimISpace2 platform (Ihrig, 2013; Ihrig & Abrahams, 2007). According to these agent-based simulation models, some strategies have been investigated to model the knowledge flow through open innovation as a business trading approach (Aversa & Ihrig, 2012; Savitskaya & Ihrig, 2012). Being more focused on commercial and economic aspects, companies traditionally look for innovation trading in terms of profit or loss, in order to obtain more market share in comparison with their competitors. Basically, in fab labs, there is no knowledge or innovation trading since it is expected to support and respond to personal expectations as an open source approach. For that reason, these knowledge sharing models cannot be used directly in this research; however, they can be considered only as general ideas to develop a theoretical model, as proposed in this work.

1.3 Research objectives

This section introduces the general and specific objectives of this research, as well as the advantages of proposed model and its contribution impact.

1.3.1 General objectives

The general objective of this research is to propose a theoretical understanding and model of how knowledge and practical experiences of Fab Lab community members are learned, diffused, and managed by individuals under collaborative learning interactions. In other words, the objective of this work is to study the performance of Fab Lab communities in various configuration scenarios, including the initial composition of skills and expertise, the availability and involvement of actors, or the learning ability of the actors.

In addition, this research aims to investigate the specific impacts of interpersonal interactions and the learning process, as well as motivation programs, which can impact Fab Labs productivity.

1.3.2 Specific objectives

In order to achieve the general objective of this research, three specific objectives are defined. The first specific objective is to design a general simulation model of Fab labs, which can be used to represent dynamic Fab Lab communities with different configurations. To do so, we will review skill-communities, similar to Fab labs, in order to determine the bottom-up organizational structure of this concept including co-creation structure and self-learning system. We will also review previous agent-based attempts in knowledge sharing to delineate the principles of the underlying theories and the essential assumptions based on individualization approach. Then, using this information, the model was programmed and simulated in the AnyLogic platform to provide a virtual tool for experimenting. In other words, the simulation model was designed in a way that can reproduce a Fab lab's environment and knowledge sharing flows. Specifically, the community is adjustable in terms of number of agents with attributes similar to real members who can interact as the main actors individually or in a group.

The second specific objective addresses the need to validate the proposed model, but mostly to investigate the impact of Fab Lab managerial methods to increase productivity. To do so, two series of experiments were planned and executed. The first series of experiments addresses the need to validate the model in a context where there is neither related empirical data nor historical variants to compare and check the results of this simulation with a real Fab Lab community. The second series of experiments evaluate the impact of motivation programs in terms of activeness level of Fab Lab communities.

Finally, the third specific objective is to propose practical recommendations to Fab Lab or any other similar skill-community managers in order to improve their strategies and policies to increase productivity.

1.3.3 Contribution impact

A comprehensive simulation, which offers a precise modeling of knowledge flows among individuals, can be a valuable academic reference for researchers in next studies on Fab lab-based businesses in different domains such as: management, logistics, finance, operation, network, etc.

Thus, Fab lab, and all other similar socio-technological notions including their communities, managers, owners, and investors, can directly benefit from this theoretical modeling research. Moreover, it can have indirect advantages for the societies in general and the governments by reducing fabrication costs and empowering individuals to do their personal technological requirements. Finally, by recommending simple solutions of how to use the local resources it can be a huge asset to the environment and nature.

1.4 Research structure

To achieve the objectives of this research, a methodological agent-based simulation is adopted, which is particularly relevant for the simulation of complex adaptive and socio-technical systems such as Fab labs. Since this research is a methodological development study, we took some major steps to achieve an acceptable result. First, a conceptual model was developed based on the theoretical models and empirical studies of the CoPs. The model was adapted to the interactions within Fab Lab communities in terms of knowledge and practical experience sharing. Based on this conceptual model, a simulation including a number of socio-technical parameters was developed and programmed in AnyLogic. Then, scenarios inspired by case studies found in the literature were designed in order to test and validate the model. Finally, experiments were specifically carried out to study various Fab Lab performance criteria as a function of the configuration factors. Besides, the final discussions on the obtained results led us to conclude this research and to recommend the possibilities of future research on this subject.

CHAPTER 2 LITERATURE REVIEW

This literature review focuses mainly on the new notion of individual production, which is particularly linked to fab labs. In order to have a better understanding of the notions implied here, it is essential to distinguish between, on the one hand, what Fab Lab introduces, and, on the other hand, what conventional production methods do. Furthermore, the informal structure of communities of practice and their impact on innovation development is reviewed in this chapter and finally it presents similar existing models.

2.1 Working space studios

The general idea of providing working spaces, tools and equipment for DIY activities has been developed in different ways. Among diverse local and international studios, fab labs, TechShops, Makerspaces, and Hackerspace are the most known examples of fabrication and prototyping service centers. Although, TechShops Corporation declared bankruptcy on February 26, 2018 (i.e., their working studios are not accessible anymore, (TechShop, 2018)), their contribution to this notion is considerable. A general review shows that they all offer collaborating, learning, and sharing environment to whom is interested in technologies, digital arts, sciences, or computers (Fabfoundation, 2018b; Makerspaces, 2018). Besides, since the price of fabrication tools and equipment became more affordable in recent years, members in each lab have access to a quite similar range of hardware, equipment, and tools including CNC, 3D printers, desktop laser cutters, mills, hand tools, power tools, and electronics tools. However, their mission and vision has made them different. For example, Hackerspaces are proper places for digital technology experts to meet and exchange their experiences; whereas, in Makerspaces non-professionals usually use the collaborative opportunities to share their skills for DIY project purposes; whilst, TechShops were membership-based private workshops for who wanted to pursue their personal projects.

In comparison with other working spaces, Fab Labs are special laboratories considering that they can have various structures with three main purposes comprising institutional fab labs, associative fab labs, and entrepreneurial fab labs. Generally, a Fab Lab can be open to the public or a particular community depending on its policy and direction (Morel & Le Roux, 2016). Different types of Fab Lab can respond to five major groups of necessities including: DIY activities, educational purposes, rapid prototyping projects, local productions (especially in developing countries), and innovations.

2.2 Fab lab

Putting aside the historical reviews of Fab Lab or other similar individualized fabrication efforts, we discuss in this section the reasons why this new concept is believed by some researchers to be an industrial revolution (Morel & Le Roux, 2016; Troxler, 2013).

Fab Lab charter defines its mission by answering to some specific questions (CBA, 2015). Here is the first question and its relevant answer:

"What is a fab lab? Fab Labs are a global network of local labs, enabling invention by providing access to tools for digital fabrication."

As it is clear, the answer started to point out the vital clue of this new concept, which is "*the global network*" connection. Most people still are enthusiastic about the role of 3D printers and the possibility of digital fabrication as the extraordinary invented tools (Gershenfeld, 2008; Hopkinson, Hague, & Dickens, 2006). On the other hand, the idea that Fab Labs are versatile small laboratories, where you can make almost anything supported by digital fabrication tools (Bull & Garofalo, 2009; Gershenfeld, 2012), is remarkable but intriguing. However, Fab Labs are not exactly that. To understand this illusory misunderstanding, we can ask a comprehensible question: did the creation of 2D printers revolutionized literature? Consequently, we can assume that the raise of 3D printers or any other digital manufacturing tools alone will not cause an industrial revolution, unless they are utilized as popular digital tools only to facilitate and simplify the fabrication processes within the whole context of Fab Lab or other similar structures. Therefore, as a quick conclusion we can indicate that the undeniable role of being connected to the global network and its community made Fab Lab as a new paradigm of manufacturing.

On the other hand, if anybody claims that connecting to the global network community is a new phenomenon in industrial fabrication, then immediately other questions come to mind such as:

- Is there any connection between the current production companies and communities?
- Are the existing fabricators and producers able to benefit from their connections with the global communities?

Accordingly, it seems essential to quickly review the latest role of global network communities in recent marketing-oriented businesses in order to better understand what really makes Fab Lab a new fabrication paradigm. In this regard, in the next section, we explain the market-oriented production approach in more details to investigate the role of communities and surrounding environment from the companies' point of view.

2.3 Marketing-oriented production

According to the principles of marketing, market-oriented businesses must use marketing information system, also known as MIS or MKIS (Armstrong & Kotler, 2011b; Goslar & Brown, 1986; Ives & Learmonth, 1984). Studying all actors and factors of the marketing environment is essential to create and maintain a proper customer relationship (Pickton & Broderick, 2001; Saad, 1995). Hence, there should be a systematic design, collection, analysis, and reporting of information obtained from both macro-environment and micro-environment surrounding any production businesses (Armstrong & Kotler, 2011a).

Close actors and communities in the micro-environment should always be under a precise and direct supervision like the company itself (i.e. the employees and the internal culture), suppliers, marketing intermediaries, customers, markets, competitors, and the public. On the other hand, the larger societal forces within the macro-environments should not be neglected such as demographic, economic, natural, technological, political, and cultural powers.

Being connected to the communities to explore all information by conducting experiments, surveying, and observation to receive updated feedbacks are the critical abilities to most modern-day manufacturers, which enables them to survive and maximize their customers' loyalty. They utilize different techniques and methods like publishing newsletters, having websites and forums, being connected to the social network Medias, and enabling and using an effective CRM in order to make a strong connection with all related communities. Therefore, they know that any external and internal actors can influence their business nature and existence directly or indirectly.

In this context, what can be the advantages of producing by individuals while they still have neither relevant experiences, nor sufficient knowledge, nor significant capital to invest, nor branding reputation to survive in the competitive business environment?

Accordingly, we need to prove that the relationship between companies and communities are different from the way that Fab labs benefit from their connections to communities in order to develop personalized fabrication. As a result, in the next section we review the steps of product development in order to investigate the nature of connection to the community.

2.4 Product development process

The fact that producers desire to be pioneer among their competitors usually leads them to invest for generating new ideas. They accept the risks and expenses to extend their target markets and gain more profit. Therefore, they need to have access to recent innovations to develop new products, modify their products, or improve current products. Product development can take one or two years for some companies since they follow their conventional systematic processes. Whereas, other companies with innovative solutions for finding, improving, or using information come up with a continuous flow of technologies and services. There are different strategies to innovate and develop new products. However, understanding customers and their actual needs is a big challenge. Accordingly, it seems that having a detailed plan followed by a step-by-step product development process is a must (Armstrong & Kotler, 2011c).

2.4.1 Generating new ideas

Finding innovative solutions, besides having a classical R&D department, is one of the critical public relation and communication responsibilities of current leader companies. For example, Cisco set up an internal Idea Zone letting its employees to propose new ideas for new products or product modifications. As a result, producers try to be in close contact with different communities in their market environment to receive more feedbacks or new ideas. They try to explore all their internal sources of ideas including the ideas coming from their employees, besides the external sources such as suppliers, distributors, or competitors. Meanwhile, crowdsourcing or open-innovation is another recent technique that attracted many companies in recent years and by which companies invite different independent sources of ideas from communities, scientists, employees, or researchers, to participate in their product innovation processes.

2.4.2 Idea screening

All activities within an enterprise serve the vision of the business owners, which defines the mission of the companies (De Wit & Meyer, 2010). In other words, companies have their own strategies and directions. Therefore, when companies receive different new ideas from their surrounding environment, only the ideas compatible with the same direction can be accepted, while the rest should be ignored (Figure 2-1). Companies always aim at meeting the needs of their customers. However, they assess these new ideas in terms of profit or loss, which may directly lead them to success or failure in the market competitions. Consequently, the main problem, which emerges from idea screening is that many of the genuine ideas and feedbacks, which are not aligned with their strategic directions, are disregarded even though they can be opportunities.

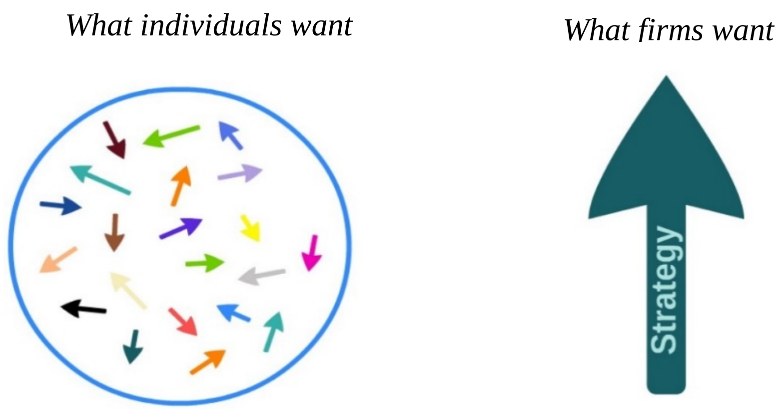


Figure 2-1: Most ideas coming from feedbacks are not aligned with the firm's direction

2.4.3 Feedback steps

More steps that must be taken in accordance with the current process of new product development are noticeable such as concept development and testing, product development, and marketing tests. Although the role of information received from contact with environments and communities is important in all steps. Nevertheless, these kinds of information are only assessed in terms of profitability. Being able to survive in the market environment, businesses must have their own portfolios with specific life cycles. Producers should have the ability to surprise their customers in order to keep their desired market share. Therefore, they have to consider the received feedbacks mostly dedicated on problem solving and modification to follow a regular continuous improvement plan to develop their updated products with new features (De Wit & Meyer, 2010).

2.5 Fab Labs production

In order to guarantee a success to launch new product, major companies try to avoid any probable risks of failure. For that reason, they usually compete to develop similar limited categories of features with complicated and secret hidden designs. Thus, this trend of top-down decision-making forces buyers by means of marketing strategies to consume more.

On the opposite side, Fab Labs and the other similar notions of production are located in the lower hierarchical levels, which results in horizontal power. On the contrary to the centralized steps in which companies try to benefit from feedbacks, in this new fabrication paradigm, the design process can happen at any time through producing or using the products. Participants from anywhere can change the design of products in accordance with their individual needs. In these sorts of personalized fabrication communities, the borders between amateurs and professionals are removed, and since collaboration, training, and creativity are collective, not only nobody needs to hide their personal ideas but also they are encouraged to share their practices and exchange values (Morel & Le Roux, 2016). What Fab Lab defines as a revolutionary idea is the productive combination of independency, digital technology, and community, which results in a pure agile system. Accordingly, it is proper to say that this technology breakthrough concept does not present any strange discovery nor any new phenomenon. It introduces how to produce individually (Do It Yourself or DIY) while being supported from communities (Do It With Others or DIWO). It can differently respond to personal requirements through open innovation with a variety of simple original designs and a drastic reduction in production costs. Therefore, it accurately can be called democratization in fabrication (Blikstein, 2013).

2.6 Communities of practice

As mentioned earlier, CoPs are the most similar systems to Fab Lab communities. I this section we review the attributes of CoPs with more in details. Communities of practices have emerged when people voluntarily join informal groups at their workplace to discuss about their common concerns or interests (Lave & Wenger, 1998; Nickols, 2003; Snyder, Wenger, & BRIGGS, 1999; Wenger, Etienne et al., 2002). Since the participants of these communities meet with each other to share and interact about their personal experiences and perceptions, it can be considered as a valuable kind of knowledge sharing system (Bate & Robert, 2002; Burk, 2000) to collect and circulate knowledge and expertise through members' interactions.

The common similarity between CoP and Fab Lab is the community; however, their organizations, objectives, and contexts are different. CoPs generally consist of professionals and mostly employees of companies. Hence, top managers create and fund CoPs to support their knowledge and innovation requirements. On the other hand, Fab Labs and other similar notions are basically created for the public to support their personal innovation, training, or fabrication requirements (Capdevila, 2013). Regardless of their differences in terms of members and purposes, both communities have the same structure in order to provide a proper environment for collaborative interactions, which can result in innovations or new ideas by knowledge circulation. Some researchers believe that special characteristics of Fab Lab communities such as openness, interdisciplinary collaboration, effectiveness, and transferability made it as a core of CoP (Troxler & Schweikert, 2010; Troxler & Wolf, 2010). Accordingly, the principles of community architecture in CoPs, which describe the different levels of participants, can be instrumental to developing a simulation model of Fab Lab communities. People with different levels of skill and knowledge participate in these kinds of communities to pursue their personal interests. However, in terms of activeness, members are categorized in three main levels in accordance with their different degrees of involvement (Wenger, Etienne et al., 2002).

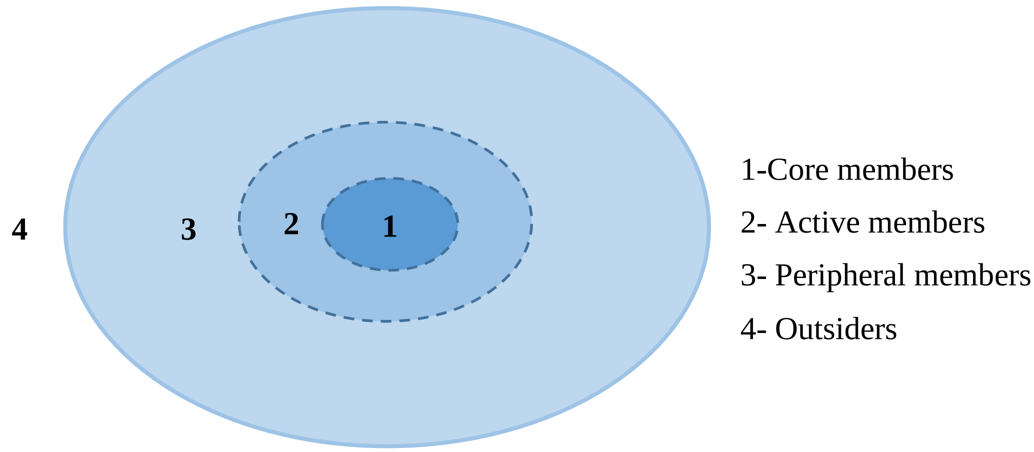


Figure 2-2: Layers of membership in CoPs (Wenger, Etienne, McDermott, & Snyder, 2002)

According to Figure 2-2, the majority of members who belong to the peripheral layer (3) prefer to participate occasionally because of the various expectations and motivations. On the other hand, core members (1) play the leadership role with a complete commitment in coordinating the community as the smallest group. There are also active members (2) who participate regularly in the community events and programs. In addition to the mentioned major layers, there are surrounding members who are interested in the communities but not as the members (4). These outsiders usually follow the communities as sponsors, suppliers, customers, etc. (Flechet, 2016). Moreover, members might not have a fixed position in a specific layer. They can change their involvement at any time so they can move from one layer to another, depending on their personal preferences and free time schedules.

2.7 Analyzing the existing models to define the project issues

Existing agent-based knowledge-sharing simulation platforms were the best point to start and have a general overlook for our research. There are several efforts to model knowledge sharing among organizations based on SimISpace2 platform (Ihrig, 2013; Ihrig & Abrahams, 2007). Also with reference to these agent-based simulations, some strategies have been investigated to model the knowledge flow through open innovation (Aversa & Ihrig, 2012; Savitskaya & Ihrig, 2012). The general knowledge sharing process explains how independent actors find each other, connect together, and interact to survive by a business trading approach. Being more focused on commercial and economic aspects, companies traditionally look for innovation trading in terms of profit or loss in order to obtain more market share in comparison with their competitors. Although conversely, in Fab Lab, and other similar notions, there is no knowledge or innovation trading since it is expected to support and to respond personal requirements as an open-source approach.

The general concept of I-Space modeling is adapted in SimISpace2 to develop an agent-based simulation of the knowledge flow. They both recreate a collaborative and competitive knowledge environment to study the knowledge flow, which includes how knowledge is generated, diffused, or managed by actors. Agents in this model can own or have knowledge entities from discovering, trading, or licensing. Since these knowledge items have certain values, agents can either spend money to buy them for self-exploiting purposes or to capitalize from their ownerships. On the other hand, the value of knowledge depends on abstraction and codification levels. More codified knowledge can diffuse easier, besides more abstracted knowledge results to more revenue. The other important factor on knowledge value is their deficiency, which represents the ability of knowledge items to diffuse and to become more applicable among agents. Financial funds are the major motivation for interaction in both models. Actors are able to do different actions, for example in SimISpace2 (Figure 2-3), in order to survive and then to increase their capital. Assuming that there is no knowledge trading through Fab Lab interactions, this analysis shows only the principle ideas and the underlying theories that can be adapted in our project. Nevertheless, the basic logic of the existing models is inspiring, given that the general objective of this project is studying the knowledge flow among the members of Fab Lab community to figure out the productivity of the system.

Simulation configurations				Simulation run	Simulation evaluation
Knowledge properties		Agent properties	Simulation properties	Actions by agents	Validation
Knowledge item	Knowledge store				
Dynamic Obsolescence Diffusion Static Obsolescence rate Base value Per period carrying cost Codification increment Abstraction increment Start in public domain	Dynamic Location X Location Y Codification Abstraction Structuring effort	Dynamic Location X Location Y Experience funds Financial funds Static Relocation distance Per period income Per period expenditure Price multiplier Activity rate Propensity to scan from ocean H Factor Vision Action properties Propensity Effectiveness Efficiency	Patent Length Patent strength Copyright length Copyright strength Exclusive license length Non-exclusive licence length Trade revenue multiplier Exclusive license multiplier Non-exclusive licence multiplier Exploit revenue multiplier Similarity function Copyright codification threshold Copyright abstraction threshold Patent codification threshold Patent abstraction threshold Pub. domain abs. diff. threshold Scan from surrounding function Agents in simulation Action properties Base financial cost Base experience gained or loss Required experience threshold	Relocate Exit Enter Relax Scan Discover Learn Exploit Dispose Codify Absorb Abstract Impact Patent Copyright Meet Trade (buy, sell) Exclusive license Non-Excl. license	A More structured knowledge diffuse faster B Knowledge that is more diffused is worth less C More structured knowledge is worth more

Figure 2-3: Structure of SimISpace2 (Ihrig, 2013)

2.8 Literature review conclusion

A community in which autonomous individuals interact in accordance to their personal preferences and in a collaborative context is a good example of a complex adaptive and socio-technological system. Based on what were reviewed in this chapter about the Fab Lab fabrication paradigm and the importance of their communities, an agent-based modeling seems to be the most appropriate method to reproduce the skill-communities as for a simulation purpose. Since it seems that there is no dynamic model to simulate the kinetic of Fab Lab the first contribution and objective of this research is to propose a model of the environment of a Fab Lab community. Next, a computer simulation program is required to simulate Fab Lab communities and study their dynamics.

CHAPTER 3 METHODOLOGY

This chapter provides a general overview about the methodological steps of this projects. First, it explains our involvement with this project from the beginning. In the second section, we talk about the general concept of the modeling and validation criteria in terms of skill levels, motivations, decision-making processes, and communication parameters. Then, we quickly review the general assumptions of this project. Computer programing of this model is the next part of this chapter. Finally, we introduce our experimental design and conclude the Chapter.

3.1 Context of the project

Our involvement in the project began in September 2016. The early discussions were about the concept of Fab Lab in general. The main objective was to analyze Fab Lab and develop a comprehensive model the optimization of their management. Considering that, there was neither previous study in this regard nor any model to study Fab Lab environment. A thorough literature review was accomplished in about six months in order to explore all similar concepts and previous efforts. Eventually, a general model was developed in four months afterwards. It was then programmed and experiments were carried out. The concept studied in this project does not address any actual issue of any existing organizations. This project is purely theoretical.

3.2 Design, modeling, and validation criteria

The existing knowledge-sharing agent-based simulations cannot be used directly in this research. This chapter discusses about the main concerns, which have to be considered in this model. As explained up to here, reproducing a Fab Lab community to study its behavior in different configurations is the principle objective of this project. Therefore, we need to define and model the concept of community further in details. The general term of community refers to a group of people with common interests who are in contact for certain reasons. This means, the actors of this simulation are people and it is not a simple job to reproduce perfectly their behavior. Thus, we try to focus only on some limited aspects of human attributes, which seems to be more involved in individual practical activities and decision-making processes. Accordingly, we need to know what exactly happens in a real Fab Lab community.

3.2.1 Skill level of members

Members of a Fab Lab have access to a range of equipment, tools, materials, and software to have practical experiences. According to what is required to setup a Fab Lab, the Fabfoundation proposes a particular list, which needs an investment of about $25-$65k for essential equipment and $15-$40k for consumables (Fabfoundation, 2018a). To be involved in such a fabrication studio, members should have or learn an acceptable level of skills to work with certain number of equipment and tools first for their safety, and then, for being able to have their individual production experiences (Table 3-1).

Table 3-1: An example for equipment, which are available in Belfast and Nerve Center Fab Labs in northern Ireland (Fablabni, 2018).

Equipment/ Tool	Application range
3D Printer	Different range for plastic based filaments
3D Scanner	Compatible outcome file can be processed in any 3D software
Electronics bench	Is equipped with different electronics components
Laser cutter	Cutting bed with 600 × 300 mm and applicable for different materials including wood, glass, acrylic, cork, and leather
Modela desktop milling machine	Compatible with 2D or 3D software for rapid prototyping purposes
Scroll saw	Applicable for variety of materials
Shop bot	Large scale (1220 × 2440 mm) CNC milling router which is compatible with different input file formats
Software	They are mostly freeware for public use such as:Gimp, Blender, Openoffice, InkScape, Sketch Up, Adobe, Qcad, Eagle, and MIT Software
Vinyl cutter	Suited for faster production and more professional looking graphics

For this reason, the first step is to design a modeling environment in which agents have independent *skill levels* for certain *number of skills*. Therefore, actors interact to increase their skill levels, while people do not learn with at a similar learning talent and speed. Thus, two other independent factors including agents' *technology talent* and their *diligence* (seriousness to pursue a goal) can influence their learning speed.

With this logic, we can conclude that community members cannot interact on practical activities unless they become familiar with the principals of the available services and learn the basic operations of the equipment in the laboratory. Concerning the model validation phase, it is quite predictable that we can expect no interaction among community members if all of them have skill levels below a certain learning level. In other words, when none of the members of a community knows how to operate an equipment, there cannot be any fabrication interaction among them involved with that equipment.

3.2.2 Motivation and decision-making of members

One of the important dynamic attributes of community members is their motivation. Unlike the existing agent-based models of knowledge flow, in an open innovative context with no competition, financial funds are not applicable, and personal interests and concerns can play the role of motivation to encourage oneself for spending more time to learn new skills, to participate in activities, and to share the achievements with other members. We have defined three independent factors in this model to refer to each community member's motivation state.

Interest level is an independent parameter, which represents the desire of an actor to participate in Fab Lab activities. *Interest level* can be different for each community member but when it comes to study the impact of other parameters in the validation phase or during experiments, we have assumed that they are fixed in time for everyone.

Expectation about each skill is the other motivation factor in this model. People in a Fab Lab community have not necessarily similar personal preferences and their priorities for available practices are different. For example, one member may expect to learn 3D scanning to a professional level, whereas other member might only be interested to become familiar with its basic applications.

The third parameter to design the motivation aspect in this model is the *minimum collective agreement*. This factor represents the desire of members when they need to make a decision as a group. If a certain percentage of a group's members agree to do an action, then their agreement can be considered as a collective motivation. In this respect, the threshold (minimum required agreement) of the collective decision-making is an independent parameter. The collective interest of a group is the outcome of the *expectation level*s of each individual (section 4.3.3).

3.2.3 Communication of members

From what was explained in the literature review chapter, community is the undeniable advantage of Fab Labs to connect members and empower them in order to support people for new experiences. Actors in this model need some specific attributes that can be referred to their connectivity and group working possibilities.

In the first step to make a connection, actors need to have access to some information about each other. By evaluating different connectivity opportunities, they can decide whether to connect to another member or stay away. In the real world, the sharing of this type of information happens when people are physically or virtually near each other and have direct contact or access to a variety of databases including social media to find other people for their connection purposes. In the analysis of existing agent-based models, agents and knowledge entities have physical locations in their simulation environment. They can also "scan" other members or knowledge stores, which are located in their neighborhood. Regardless of how Fab Lab members have access to the information about each other by physical meetings or virtual connections, this model defines an independent *communication accessibility* factor. When this parameter is 100%, it means that each member has access to any of other members and members are free to find their connections from the entire community population. On the other hand, when the accessibility is 0%, members do not have any information about others, implying that they can only participate in the Fab Lab individually. Different values of this parameter can be used to validate the model in terms of group working. It is expected that individual working should be less probable than group working when the model is configured with high level of communication accessibility.

In general, agents can decide personally to make connections with other agents who they find interesting. This interest can appear in accordance to their personal priorities. Some agents are interested in agents with similar qualifications, whereas others are interested to communicate with agents with dissimilar qualifications. The idea of using *Homophily* to create connections is inspired by existing agent-based models with some modifications (Ihrig, 2013). In this model, the average difference between the expectation about each skill of an agent and its actual skill level is called the *H-factor* of that member. The general logic to connect members in this model is developed based on this parameter. A positive *H-factor* means that a member wants to meet other actors whose average of skill levels is more than her/his average expectation level. In other words, only professionals are interesting to members with positive *H-factor*. On the other hand, negative *H-factor* means that an agent prefers to meet members with an average skill level lower than her/his average expectation level. So, only beginners and less skillful members are interesting to actors with negative *H-factor*.

The last important factor, which is used in this model to design the connectivity of Fab Lab members, is a psychological parameter. It is widely acknowledged that extrovert people have more tendency to extend their network and communication because of their personality (Correa, Hinsley, & De Zuniga, 2010). Conversely, introvert people seem to be difficult to connect with. But what is imperative in this model is the communication between introverts and extroverts (Thorne, 1987). In other words, people with similar extrovert personalities do not communicate properly, while very dissimilar personalities do not interest each other as well. In this model, *similarity factor* defines the difference between *extroversion levels* of each two members. If this factor value is within an acceptable range for any two members, then they can meet and decide whether to communicate or not, otherwise there is no chance to meet.

3.3 General assumptions

The previous sections showed that the initial design phase first focused on modeling options, making references to existing models from literature review. On the other hand, other aspects of this project were never addressed in the literature. Thus, we made some necessary assumptions to carry out this simulation.

3.3.1 Community environment

In the previous sections, we talked about community in general. Here, we define it more precisely with clear assumptions:

- Members do not have any personal preferences or issues such as psychological, sexual, racial, or political;
- There is no cultural, social, linguistic, or age barriers for the communications;
- The community is a homogeneous system in which members make connections and communicate together only for fabrication purposes. Furthermore, we assume that their behavioral pattern do not change during the community lifespan;
- Social interaction types (extrovert and introvert), which are inspired by Myers-Briggs Type Indicator, are used to initiate interactions between agents;
- There is no human feeling motivation in the relations and interactions;
- Participants in this community can decide and interact autonomously only based on their own states of attributes and other members cannot influence them;
- A community comprises certain number of members.

3.3.2 Skill level

Each member in the community has a set of skills, each of which can be improved during interactions while following its own individual Logistic S curve as the learning curve (see section 4.1).

Members are categorized into four groups in terms of their skill levels (Table 3-2). For example, one member can be master in a skill, while at the same time having a learning level in another skill. Next, certain actions are defined for members in each category (Table 3-3).

Table 3-2: Categories of community members in terms of their skill levels.

Skill category	Interval of skill level
B (Beginning)	$0 \leq$ Skill level ≤ 0.05
L (Learning)	$0.05 <$ Skill level ≤ 0.20
P (Practicing)	$0.20 <$ Skill level ≤ 0.80
M (Master)	$0.80 <$ Skill level ≤ 1.00

Table 3-3: Members' possible actions for each skill based on the level of that skill

Action	Which members can do the action?				Condition
	B	L	P	M	
Teaching	-	-	✓	✓	(M): If there is no other master member in the group for that skill (P): If there is no other member with master or practicing level in that group for that skill.
Learning	✓	✓	✓	-	Only if there is an instructor (teacher) in the group
Interacting	✓	✓	✓	✓	If there are at least 2 masters or 2 members with practicing level
Working individually	-	-	✓	✓	If they do not have any connections.

3.3.3 Interactions

In this model we reproduced only two types of interactions, which are explained in details in the next chapter. The first group of interactions are peer-to-peer, which may happen only between members that have *communication accessibility* (see section 3.2.3). Members in different community divisions cannot interact with each other at all. In other words, division can represent any communication constraints. For instance divisions can be several labs in different geographical locations. The second group of interactions may occur between an individual and a group of members. In this type of interactions, groups and individuals can be located in different communication divisions. What is important here is that the internal interactions of the group must be *cooperation learning/teaching* (Table 3-4). A teacher whose skill level is more than the rest of the group members has to be in any *cooperative learning/ teaching* group. So other members can learn from her/him. However, in a group with *collaboration* interactions, members can improve their skill levels from discussions.

Table 3-4: Types of group interactions based on the number of participants and their skill levels.

Internal interactions in a group	Number of participants in each group and their skill levels			
	B	L	P	M
Cooperative learning/ teaching	any	any	any	only 1
	any	any	only 1	0
Collaboration	any	any	any	at least 2
	any	any	at least 2	0

3.4 Computer programming

At the beginning of the research, we did not have a preference to use any specific platform for the programming phase. When the model was completed, we faced a multitude of independent factors and functions that should be coded. Therefore, AnyLogic was chosen because of its capacity to include Java programming. Indeed, the complexity of the model required a versatile platform. To build the model, we consulted the published book by AnyLogic company (Grigoryev, 2015), besides several courses available online. These sources were only sufficient to become familiar with the AnyLogic general features and capabilities. The advantage of using Anylogic was that it accepts Java commands. Therefore, we decided to use AnyLogic only as a platform and do all programming phase with Java codes. Learning Java source coding was helpful and it took a while to review the language's syntax rules. We understood that it is highly recommended to implement complex models. Consequently, the whole model was divided in separate modules and was programed with Java codes. This procedure helped us to verify each part of the simulation individually to avoid any logic errors. Furthermore, whenever the input data were not sufficient, we could define adequate detailed assumptions to clarify the system functionality.

3.5 Design of experiments and conclusion

Once the model was programmed and was verified (i.e., make sure each programmed function were working as intended), we planned experiments for two general purposes (see chapter 5 for more details). The first parts of the experiments aimed at validating the model since there is no related empirical data from a real Fab Lab community. To do so, the following aspects of Fab Lab communities were studied through a series of experiments:

- Active lifespan;
- Level of activeness;
- Transferred skill/ knowledge;
- Individual interactions;
- Group interactions;
- Passive members through interactions.

Second part of the experiments aims at testing an optimization procedure in order to recommend practical solutions to Fab Lab managers to improve the level of activity and lifespan of the Fab Lab. In other words, we study the impact of motivation programs on the behavior of the Fab Lab community.

Finally, the last chapter of this thesis discusses the results obtained. Considering the assumptions, it explains how different parameters can influence the functionality of the skill-communities for different strategies and Fab Lab missions. It also proposes some recommendations for Fab Lab managers and suggests some future studies for researchers.

CHAPTER 4 AGENT-BASED MODEL DESIGN

This Chapter specifies how our model is designed to reproduce a Fab Lab community. It also includes the mathematical expressions to explain the logic of internal processes, which are used in the programming phase. The first section describes the whole environment of a community and defines the details in terms of parameters and variables. Agentification is the next section that defines the actors of this model. Next, we present the rest of the model in details. Accordingly, the third section of this chapter details the model's dynamic in order to illustrate the behaviors and attributes of the agents and their interactions. The forth section discusses the results of the interactions. Finally, we evaluate the validity of this model and the acceptable conditions, under which we can use it for the final series of experiments.

4.1 General description of the model

According to the general assumptions of this project (section 3.3), a community comprises *N* number of autonomous members who interact together. Each member has a different skill level for the *M* skills with different personal individual expectation.

$n \in N$ Set of members;

$m \in M$ Set of skill items;

S_{nm}^{t} Level of skill *m* for member *n* at time *t* with a value ∈ [0, 1];

X_{nm} Expectation of member *n* for level of skill *m* with a value ∈ [0, 1].

The expectation is a particular individual expectation about each skill. It describes a member's desire to improve a skill. Based on our assumptions, people participate in a Fab Lab community to improve their skill levels in accordance with their personal interests. Different members can have different expectations about similar skill. Likewise, each member can have different expectations about different skills. In this model, and during the validation experiments, expectation is a personal preference, which is constant throughout the simulation and does not change through interactions. During the second series of experiments, expectation can change only by means of motivation programs. Therefore, we do not follow the members' expectation levels through the simulation run time. Unlike the expectation levels, skill levels are dependent variables. They may have initial values at the beginning of the simulation to reproduce communities with different setups, but they change through the interactions of members. In this model, it is assumed that each skill level follows its unique Logistic S curve pattern (see section 3.3.2), which may increase through interactions (Figure 4-1).

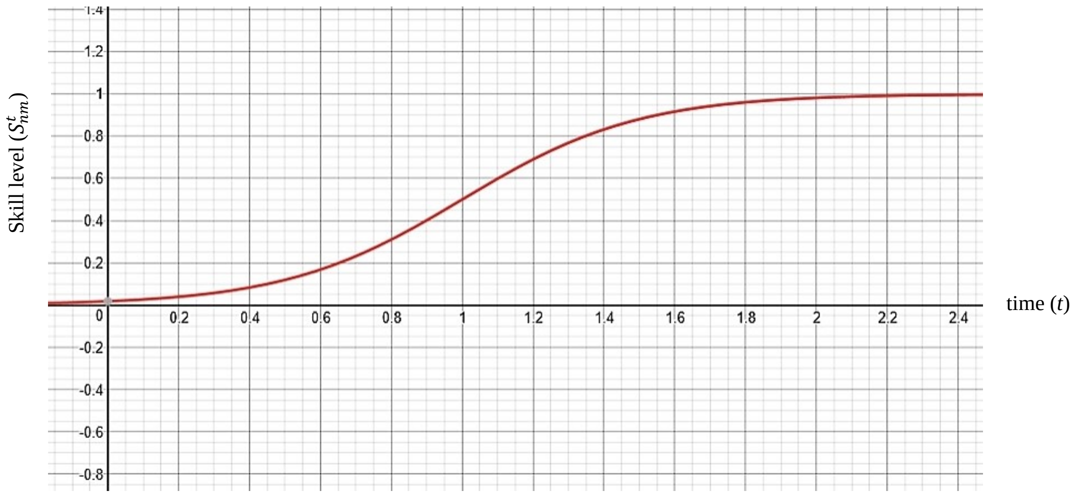


Figure 4-1: A sample S curve, which shows the improvement pattern of a skill level (S_{nm}^{t}) at any time (t).

Here, the improvement of skill levels of member m for skill n is defined as:

$$S_{nm}^{t_{nm}+1} = \frac{1}{1+e^{-V(t_{nm}-Mid_{nm})}} \tag{4-1}$$

Where V is the steepness of the curve and calibrated by trial and error:

$$V = 1.8(F_m \times Y_n \times D_n)^{1/3} + 0.2 \tag{4-2}$$

F_m	Easiness of the skill item m with $F_m \in [0, 1]$
Y_n	Technology talent of each member n with a value $\in [0, 1]$
D_n	Diligence of each member with a value $\in [0, 1]$

And at the value of $t_{nm} = 0$ the S curve formula from (4-1) gives the midpoint:

$$Mid_{nm} = \frac{\ln(\frac{1}{S_{nm}^{T=0}}-1)}{V} \tag{4-3}$$

To obtain the dependent S curve for each skill of each member, we used three independent parameters in the above-mentioned formula. Parameters Y_n and D_n are assumed to represent the personality of members, whereas F_m shows the level of easiness of that skill. These three parameters together define the steepness of the S curve. The values of these parameters are considered as the experiment configurations, which are assumed at the beginning of each simulation run to setup the community. Furthermore, $S_{nm}^{T=0}$ which shows the initial level of skill *m* for member *n* is used to calculate the S curve midpoint.

Now that we defined the general skill improvement pattern of each member for each skill, this paragraph explains the impact of t_{nm} (time) in the S curve formula. The dependent variable *t* here does not represent the simulation time. It is a cumulative time that shows how much member *n* interacted for skill *m*. Regardless with whom they interact, members devote their time using a priority rule. In other words, a member spends more time for her/his more desirable skill.

$$t_{nm} = (I_n \times X_{nm}) / (\Delta T \times \sum_{m=1}^{M} X_{nm}) \quad (4\text{-}4)$$

with

ΔT	Simulation time period in which we calculate t_{nm} (In this simulation, we calculate the active interaction time for the period of 7 days)
I_n	Interest level of member *n* to participate in Fab Lab activities with a value ∈ [0, 1]
$\sum_{m=1}^{M} X_{nm}$	Sum of all expectations of all skill *m* of member *n*, only for the skills that member *n* interacted during ΔT, which includes skills from *peer-to-peer* connections ($Vptp_{nm}$) or from *group-to-individual* interactions ($Fgti_{nm}$) (see section 4.3.3 and 4.4)

4.2 Conceptual model

Based on the agent-based modeling concept, it is necessary to define proper agents and their attributes. Given that agents have to be autonomous actors in their actions, they can communicate with each other and interact according to some behavioral patterns. On the other hand, they need to be reactive by perceiving their environment and trying to adapt themselves to changes in their environment, besides having internal goals and proactive behaviors. After reviewing different agent candidates, we chose two types of agents including:

- Individual agent type
- Group agent type

The first type of agents represents members who may interact together as independent individuals. However, agents can also be involved in the community individually with no peer-to-peer interaction. In this condition, they only utilize the Fab Lab facilities for their personal production experiences. Individuals may interact with other members in a form of group as well as interact with groups of members that have internal *cooperative learning/teaching* activities, which are open to interact with other individuals (see section 3.3.3). In addition, it is assumed that the number of members does not change (does not increase) during the simulation. In other words, members do not join or leave the Fab Lab. This simplification allows us to study the internal dynamics of Fab Labs regardless of their capacity to attract new members. However, their status may become passive when all of their skill levels meet their expectation levels. In other words, when they do not have enough motivation to interact anymore. We denote B_n as the indicator that shows that agent *n* is passive as below:

$\forall\, n \in N, \forall\, m \in M$

$$B_n = \begin{cases} 1 & if \quad S_{nm}^{t} \geq X_{nm} \\ 0 & \quad Otherwise \end{cases} \tag{4-5}$$

The second category of the agents in this model is the group type agents. Groups do not interact together. They can decide to interact only with other individuals based on their internal decision-making process. Generally, there are two types of group and only groups with *learning/teaching* internal activities (see section 3.3.3) are considered as the second type of agents (Figure 4-2).

As long as an individual agent has at least one skill level less than its expectation level for that skill, it is considered as an active agent. We denote A_n as the indicator that shows that agent *n* is active with the following condition:

$\forall\, n \in N, \exists\, m \in M$

$$A_n = \begin{cases} 1 & if \quad S_{nm}^{t} < X_{nm} \\ 0 & \quad Otherwise \end{cases} \tag{4-6}$$

Active agents are interested to participate in the interactions of the Fab Lab community. First, active agents try to find connections to work in a group. If they cannot find any connection and their level of skill is in the *Practicing* skill category, then they can interact individually (Table 3-3). Inv_n^t is the parameter that we used to show the individual involvement status of agent *n* at simulation time *t*, as defined below:

$\forall\, n \in N$

$$Inv_n^t = \begin{cases} 1 & if\ (\forall\, p \in P \mid n \notin p) \wedge (\exists\, m \in M \mid 0.2 < S_{nm}^t < X_{nm}) \\ 0 & if\ (B_n = 0) \wedge (\exists\, p \in P \mid n \in p) \end{cases} \tag{4-7}$$

Where, P is a set of groups and p represents a group of agents in which agents may interact.

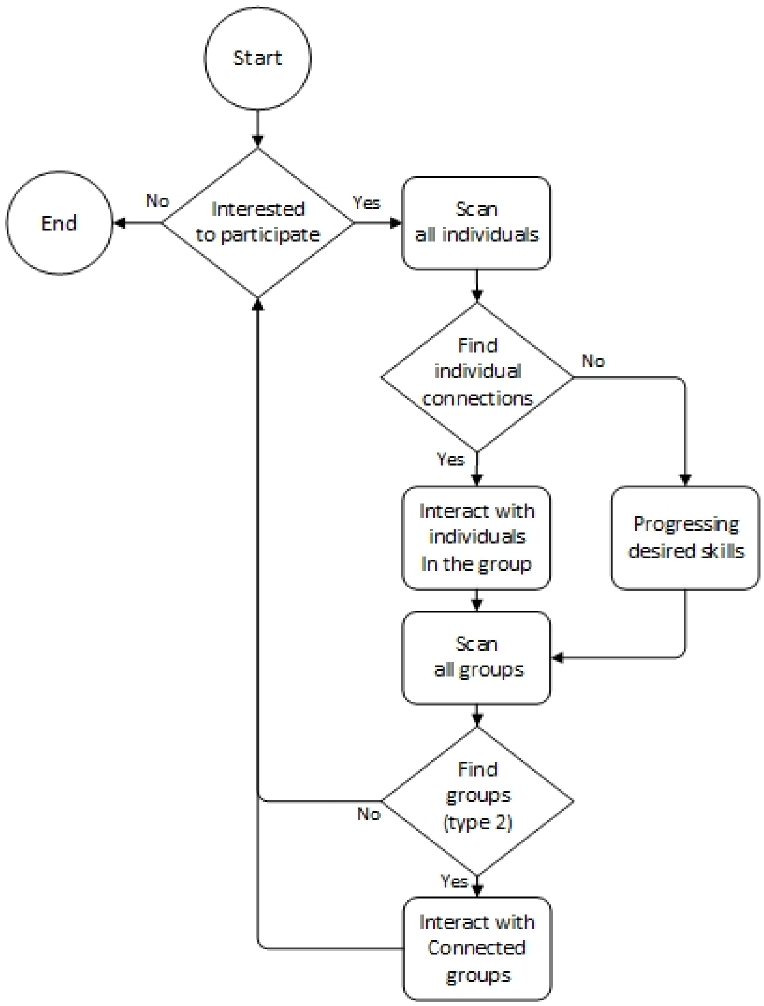


Figure 4-2: General process of agents' interactions in Fab Lab community.

If an agent has neither connection with other individuals to interact, nor sufficient skill level to practice individually, the last chance for that agent to improve is to find a connection with a group, otherwise it becomes passive until the status of other individuals changes through their interactions.

4.3 Peer-to-peer connections

In this section we clarify how each individual assesses other community members in terms of their personality, skillfulness, and connectivity in order to decide whether to join them and have interactions with them or not.

4.3.1 Scan other individuals

Each agent aims to communicate with others based on its personal motivation and decision-making parameters (section 3.2.2). To model this general idea, in the first step, the community population is divided randomly in groups according to the initial setup of communication accessibility factor (*Ca*) (section 3.2.3). Each agent has the possibility to connect with other agents who are only located in the same population division. As we explained in section 3.3.3, divisions represent communication constraints and they are different from groups. Then agents start to scan other members in terms of mutual *H-factor*s (*Hf*), which can be defined as:

$$Hf_n^t = \sum_{m=1}^{M}(X_{nm} - S_{nm}^t)/M \qquad with\ Hf_n^t \in [-1, 1] \tag{4-8}$$

In other words, Hf_n^t shows the mean difference between all expectation levels and actual skill levels of agent *n* at time *t*.

Once the *H-factor* of the agent is calculated, the agent tries to find all potential connections. To do so, each agent scan all other agents in the same population division by evaluating its *attraction towards each agent*. This attraction level (between agent *i* and agent *j*) Ae_{ij}^t is calculated as follow:

$$Ae_{ij}^t = \sum_{m=1}^{M}(S_{jm}^t - X_{im})/M \qquad with\ Ae_{ij}^t \in [-1, 1] \tag{4-9}$$

Using the *H-factor* (Hf_n^t) and the *Attraction evaluation* (Ae_{ij}^t), agents find all their potential connections. In other words, two agents *i* and *j* are potential connections if:

$$(Hf_i^t < 0 \wedge Ae_{ij}^t < 0) \vee (Hf_i^t > 0 \wedge Ae_{ij}^t > 0) \vee (Hf_i^t = 0) \tag{4-10}$$

It means, if the mean of expectation levels of an agent is less than the mean of all its actual skill levels (negative *H-factor*), the agent prefers to connect with other agents that have the mean skill levels below its expectation levels (the mean of all its expectation levels). On the other hand, if the *H-factor* of an agent is positive that agents prefers to connect with other agents with higher mean skill levels than its expectation levels (the mean of all its expectation levels). In case an agent has an *H-factor* equal to zero, it can potentially connect to all other agents.

Next, the *connectivity intensity* (Coi_{ij}^{t}) is calculated for all potential connections as follow if they are potential connections:

$$Coi_{ij}^{t} = \begin{cases} \left| \left(\sum_{m=1}^{M} \left(S_{jm}^{t} - X_{im} \right) / M \right) \times \left(\sum_{m=1}^{M} \left(S_{im}^{t} - X_{jm} \right) / M \right) \right| & if\ i \neq j \\ 0 & otherwise \end{cases} \tag{4-11}$$

The output of this step is a specific vector of potential connections (Vpt_n) for each agent (e.g. agent *n*) which includes the values of the connectivity intensity between agent n and all other agents, which can be shown as:

$$Vpt_n^t = (Coi_{n1}^t, Coi_{n2}^t, Coi_{n3}^t, \dots, Coi_{nN}^t) \tag{4-12}$$

with *N* being the total number of agent. Agents also scan the entire community in terms of their psychological *Extroversion levels* to find all possible communications.

E_n	Extroversion level of member *n* with $E_n \in [0, 1]$
ΔE_{ij}	*D*ifference between extroversion levels of two agents *i* and *j*, which we call *similarity factor, with* $\Delta E_{ij} \in [-1, 1]$
Minvert	Minimum required Extroversion difference for a proper communication
Maxvert	Maximum acceptable Extroversion difference for a proper communication

Two agents can communicate properly if

$$Minvert \leq |\Delta E_{ij}| \leq Maxvert \tag{4-13}$$

The output of this assessment is a binary vector of possible connections, Vps_n, for each agent *n*. If the *similarity factor* between agents *i* and *j* is in the acceptable range, then the value of their possible connection is 1, otherwise this value is 0.

4.3.2 Find individual connections

Using the indicators calculated in the previous section, each agent has a vector for the potential connections (Vpt_n) and a vector to show the possible connections (Vps_n). In this step, agents compute their vector of final connections, Vfc_n, in order to form groups for their interactions as shown below:

$$Vfc_n = Vpt_n \times Vps_n \tag{4-14}$$

Then, each agent chooses the connection with highest value from the list of final connections (Vfc_n). If there are more than one other agent with similar maximum values, only one of them is chosen randomly as the final connection for each agent. Each agent has only one final connection, yet each agent can be the final connection for more than one agent (Figure 4-3).

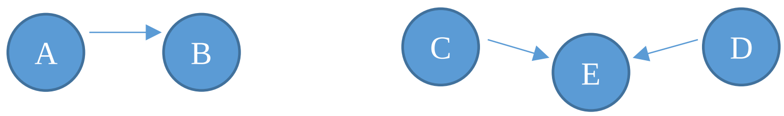


Figure 4-3: Agent B is the final connection of only one agent (agent A), whereas agent E is the final connection for two agents (agent C and agent D)

Finally, by a simple algorithm we can follow the chain of connections and assign all of the agents in sequential connections to a group (Figure 4-4). The output of this step is the groups of agents.

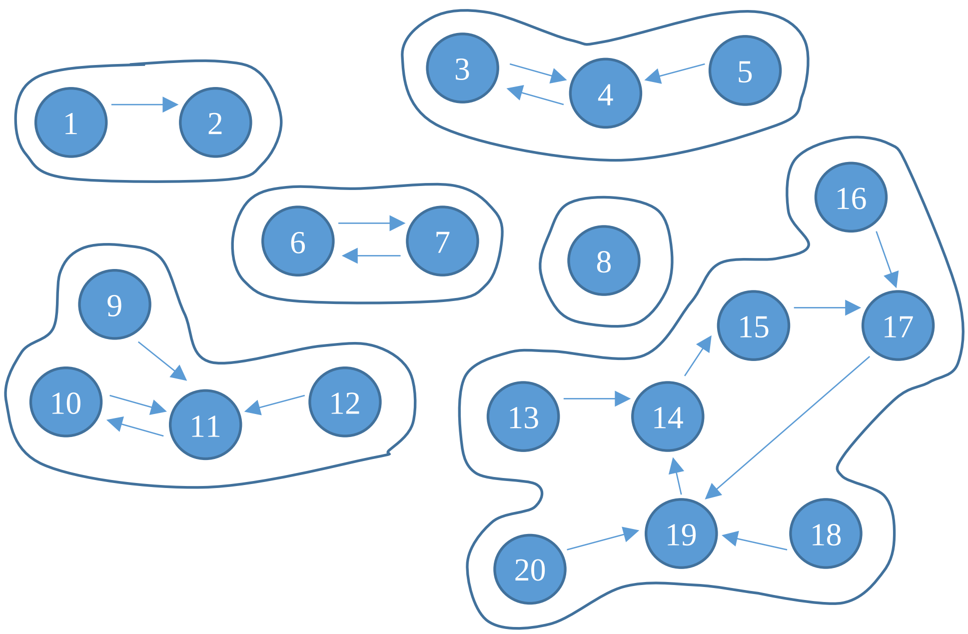


Figure 4-4: A schematic grouping in a community with 20 members.

4.3.3 Peer-to-peer interactions

Once agents found their connections and formed groups, they can interact only with their groupmates under specific circumstances. Agents from different groups cannot interact with each other at all.

P Set of groups

p Group of agents in which agents may interact with $p \in P$

$\bar{p}$ Number of members in group p with $\bar{p} \in [1, N]$

The value 1 for $\bar{p}$ means that the group has only one member and that agent may involve in the Fab Lab environment individually to practice or utilize the available facilities for its personal exploitations and purposes. To understand the interactions of agents in a group, we need to know their collective interest about each skill and compare it with the threshold of *minimum collective agreement* parameter (section 3.2.2). Then by applying the general assumptions of this model (Table 3-3 and Table 3-4), we can define the exact actions of group p towards any skill items. We use the personal interest of each group participants for each skill (SI_{nm}^{t}) to calculate the collective interest of the group CI_{pm}^{t}. CI_{pm}^{t} represents the percentage of group p members who are interested to have an interaction over skill m. If this percentage is more than the *minimum collective agreement* parameter (MCA_{pm}) then the group can have collective interaction over that skill under the conditions presented in Table 4-1. SI_{nm}^{t} is the interest of agent n to interact over skill item m. For all group members with expectation level more than the related skill level it gives a value equal to one and for skills with lower or equal expectation level than the actual skill level it receives a value equal to zero. Then by calculating the average of individual interests (SI_{nm}^{t}) of all group members, we can obtain the collective interest of that group for a skill item.

$$\forall\, n \in p: \quad SI_{nm}^{t} = \begin{cases} 1 & if \quad X_{nm} > S_{nm}^{t} \\ 0 & \quad\;\; X_{nm} \leq S_{nm}^{t} \end{cases} \tag{4-15}$$

CI_{pm}^{t} Collective interest of members in p towards skill m at time t with $CI_{pm}^{t} \in [0, 1]$

$$CI_{pm}^{t} = \sum_{n=1}^{N} \frac{SI_{nm}^{t}}{\bar{p}} \tag{4-16}$$

MCA_{pm} Minimum collective agreement of p to interact for skill m with $MCA_{pm} \in [0, 1]$

Table 4-1: Types of collective interaction towards any skill (m) in p. In any other conditions that are not listed in this table, agents do not interact and they are considered passive for that skill item.

Collective interaction towards skill m	$\bar{p}$	Number of group members with different Skill levels				CI_{pm}^{t}
		B	L	P	M	
Individual involvement	$\bar{p}$=1	0	0	1 with $SI_{nm}^{t} = 1$	0	$CI_{pm}^{t} = 1$
Individual involvement	$\bar{p}$=1	0	0	0	1 with $SI_{nm}^{t} = 1$	$CI_{pm}^{t} = 1$
Cooperative learning/teaching	$\bar{p}$ >1	any	any	any	Only 1 agent with $SI_{nm}^{t} = 1$	$MCA_{pm} \leq CI_{pm}^{t}$
Cooperative learning/teaching	$\bar{p}$ >1	any	any	Only 1 agent with $SI_{nm}^{t} = 1$	0	$MCA_{pm} \leq CI_{pm}^{t}$
Collaboration	$\bar{p}$ >1	any	any	any	At least 2 agents one with $SI_{nm}^{t} = 1$	$MCA_{pm} \leq CI_{pm}^{t}$
Collaboration	$\bar{p}$ >1	any	any	At least 2 agents one with $SI_{nm}^{t} = 1$	0	$MCA_{pm} \leq CI_{pm}^{t}$

Now that all members of a group know exactly their collective opinion for each skill, they collectively can decide to ignore some of the skills and focus only on some others for their common interaction. Given that a group is not allowed to have collaborative and cooperative activities at the same time, they can choose one of them based on their *collective expectation* (β_{pm}) for each skill item m. The process of choosing what to do in a group as a collective interaction is like a voting system. Agents know their total expectation about the set of skills, which are involved either in *collaborative activities* or in *cooperative activities*. Whatever has a higher value represents the collective priority of the group. This is calculated as follows:

L_p Set of skills that p considers as *collaborative activities* (according to Table 4-1)

H_p Set of skills that p considers as *cooperative activities* (according to Table 4-1)

β_{pm} Collective expectation of members in p for skill m

$$\beta_{pm} = \sum_{n=1}^{\bar{p}} \frac{X_{nm}}{\bar{p}} \tag{4-17}$$

α_{L_p} Collective expectation of members in p for *collaborative activities* (L_p)

$\overline{L_p}$ Number of skills that p considers as *collaborative activities*;

$$\alpha_{L_p} = \sum_{n \in p} \sum_{l \in L_p} X_{nl} \, / \, (\overline{L_p} \times \bar{p}) \tag{4-18}$$

α_{H_p} Collective expectation of members in p for *cooperative activities* (H_p)

$\overline{H_p}$ Number of skills that p considers as *cooperative activities*;

$$\alpha_{H_p} = \sum_{n \in p} \sum_{l \in H_p} X_{nl} / (\overline{H_p} \times \bar{p}) \tag{4-19}$$

A simple comparison between $\alpha_{L_p}$and α_{H_p}reveals the final decision of group p. The one that has a higher value is considered as the final activity of the group. In case, both of them have the same value, one of them is chosen randomly as the final decision.

Agents who do not have any connection and work individually use the same logic but in a much simpler way. They do not need to decide between two types of interaction options for participating in a Fab Lab. For each skill for which their interest $SI_{nm} = 1$ and a skill level $S_{nm}^{t} \geq 0.2$, agent can be involved and practice individually (Table 4-1).

The output of *peer-to-peer* interactions in a group, no matter the size of the group (i.e., one member or more), is the vector $Vptp_n$ of interacted skills by agent *n* from a *peer-to-peer connection*, which defines the skills that are involved in the interactions. Each element of this vector is outlined as $Vptp_{nm}$ to show whether or not agent *n* interacted on skill *m* through its *peer-to-peer connections*.

$$Vptp_n = (Vptp_{n1}, Vptp_{n2}, Vptp_{n2}, \dots, Vptp_{nM}) \tag{4-20}$$

This list of interacted skills is applicable for all group members. Later, these skills will be added to the list of *group-to-individual* interactions in order to distinguish between all interacted skills for each agent during any simulation time period *t*. Eventually, the progression of each skill for any agents can be calculated according to what we discussed, which can be written as:

If an agent is individual without connection

$\forall \, n \in N, B_n = 0;$

$$Vptp_{nm} = \begin{cases} 1 & if \quad (SI_{nm} = 1 \quad \wedge \quad S_{nm}^{t} \geq 0.2) \\ 0 & Otherwise \end{cases} \tag{4-21}$$

If $\alpha_{L_p} \geq \alpha_{H_p}$ (a group with collaborative activities)

$\forall\, n \in p, \forall\, m \in M$

$$Vptp_{nm} = \begin{cases} 1 & if \quad (m \in L_p) \\ 0 & Otherwise \end{cases} \tag{4-22}$$

If $\alpha_{L_p} \leq \alpha_{H_p}$ (a group with cooperative activities)

$\forall\, n \in p, \forall\, m \in M$

$$Vptp_{nm} = \begin{cases} 1 & if \quad (m \in H_p) \\ 0 & Otherwise \end{cases} \tag{4-23}$$

4.4 Group-to-individual connections

There is another type of connections in Fab Lab, which provides the opportunity to members to connect with other groups instead of individuals. When a group decides to share its achievements publicly (through Fab Lab community), or respond to other individuals regardless of their personal preferences, it is considered as an *open group*. In the model we propose in this work, all groups with internal *cooperative activities* are assumed as open groups. Unlike *Peer-to-peer* connections, members can connect to *open groups* from different population divisions regardless of the initial setup of *communication accessibility factor* (section 3.2.3). Moreover, in this sort of connections, the decision is up to individual agents whether to connect to an *open group* or not, based on their current connections and interests. Any agent who is already involved in any other types of connection can connect only to one *open group*. The difference between SI_{nm} and $Vptp_{nm}$ is used to reveal whether or not agent *n* has other interests to pursue besides its individual activities or *peer-to-peer connections* (Table 4-2). This leads to the calculation of the vector of desired skills to be interacted by agent *n* through *group-to-individual* connections, as:

$\forall\, n \in N$

$$Vgti_n = (Vgti_{n1}, Vgti_{n2}, Vgti_{n3}, \dots, Vgti_{nM}) \tag{4-24}$$

Each element of vector $Vgti_n$ is outlined as $Vgti_{nm}$ to show whether or not agent *n* interested to interact on skill *m* through *group-to-individual* connections

With

$\forall\, m \,\in\, M$

$$Vgti_{nm} = \begin{cases} 1 & if \quad (SI_{nm} - Vptp_{nm} = 1) \\ 0 & \quad Otherwise \end{cases} \tag{4-25}$$

Agents know their desired skills to interact through *group-to-individual* connections ($Vgti_{nm}$); therefore, they need to scan among available *cooperative groups* in order to find the proper group to interact with. All agents assess each *cooperative group* based on its internal interactions ($Vptp_{pm}$). If an agent desires a skill and a group can offer that skill, it is considered as an available connection for agent *n* through *group-to-individual* connections, and is referred to as $Agti_{pm}^{n}$, defined as:

$\forall\, p \,\in\, P,\ \forall\, m \,\in\, M,\ \forall\, n \,\notin\, p$

$$Agti_{pm}^{n} = \begin{cases} 1 & if \quad (Vgti_{nm} - Vptp_{pm} = 0) \\ 0 & \quad Otherwise \end{cases} \tag{4-26}$$

The group $p \,\in\, P$, which can offer the highest number of available skills ($\overline{Agti_{p}^{n}}$), is the *group-to-individual* connection of agent *n*. If there are more than one similar group with the highest $\overline{Agti_{p}^{n}}$, one of them is chosen randomly as the final connection. If the values of $\overline{Agti_{p}^{n}}$ for all groups are equal to zero, that agent does not have any opportunity to connect with a group.

$$\overline{Agti_{p}^{n}} = \sum_{m=1}^{M} Agti_{pm}^{n} \tag{4-27}$$

Finally, the available skills ($Agti_{pm}^{n}$) obtained from the group p with maximum value of $\overline{Agti_{p}^{n}}$, is the final list of interacted skill, $Fgti_{nm}$, of agent *n* for the second type of interactions, from a *group-to-individual connection*

$$Fgti_{n} = (Fgti_{n1}, Fgti_{n2}, Fgti_{n3}, \dots, Fgti_{nM}) \tag{4-28}$$

To calculate the progress of each skill of any agents, we use both lists of skills from *peer-to-peer* interaction and *group-to-individual* connections, and we use the skill's S-curve (see section 4-1).

Table 4-2: Rules to calculate $Vgti_{nm}$, which represents whether or not an agent is looking for new connections through available group-to-individual connectivity opportunities.

$Vgti_{nm}$	Conditions		
	SI_{nm}	$Vptp_{nm}$	Decision-making reasoning
0	1	1	Agent already has connections ($Vptp_{nm} = 1$) for its desire to interact ($SI_{nm} = 1$) So it does not look for new connections.
1	1	0	Agent does not have connection ($Vptp_{nm} = 0$) for its desire to interact ($SI_{nm} = 1$). So it looks for new connections.
0	0	1	The agent may be or not involved in connections ($Vptp_{nm} = 1/0$), but it does not have a desire ($SI_{nm} = 0$) to look for new connections.
0	0	0	Agent has neither connections ($Vptp_{nm} = 0$) nor any desire ($SI_{nm} = 0$) to interact.

4.5 Validation of the proposed model

This model is developed and programmed with AnyLogic platform to simulate the Fab Lab community. Then, with respect to the general concept of the model, the accuracy of each module of computer simulation was verified. Next, a general validation of the model was performed to obtain a qualitatively acceptable degree of confidence. The stability of the model was also assessed. Finally, two series of experiments were carried out to study the impact of various controllable parameters on Fab Lab community, which are explained in the next chapter.

4.5.1 Verification of the computer program

In order to avoid having errors and unreliable results, (Kleijnen, 1995) recommend verification techniques. For instance, instead of using the standard features of AnyLogic, object-oriented Java coding language was used to program the model in traceable modular sections. Next, variety of possible input settings were examined in the forms of flow diagrams to inspect the logical outputs of each module, besides using the available debugger tools. With reference to other verification methods, simulation also includes simple animations to visualize its outcomes with analytical charts to display the data generated during the simulation runs.

4.5.2 General validation techniques

Since there is neither related empirical data nor historical reports available, which could enable us to compare and check the results of this simulation with a real Fab Lab community, the accuracy of this model was validated according to methods recommended in (Kleijnen, 1995; Sargent, 2007).

The first and most important evaluation point of view was the validation of conceptual model. Comparing this proposed model with other existing similar models might help us to define the underlying theories and assumptions. However, those available simulations offered a knowledge transfer system with knowledge trading approaches, which are not applicable in our context. In this regard, only the general ideas and principles of the knowledge transfer were adapted and their trading and business notions substituted with the concept of individual interests and interactions within Fab Lab communities (section 2.7 and section 3.2).

The next step consisted in the operational validation to assess the general behavior of the proposed model, which was completed according to a combination of five following techniques. Figure 4-5 demonstrates the general outcomes of the model, which is used for operational validation skill for a community with 15 members interacting on 10 number of skills. It shows the lifespan of the community until all members become passive having different skill levels.

1- *Traces* were the first operational evaluation step. In order to detect the reliability of the model in terms of both logic and accuracy, we had several meetings to discuss about details of each specific attribute. We traced all attributes and behaviors of the model and the agents both individually also in the context of model.

2- According to the model assumptions, it is clearly predictable that if all community members have an average level of skill equal to 1 or between 0 and 0.2, there cannot be any interactions between them in any conditions (see section 3.2.1 for more details). Hence, these particular input values are appropriate for *extreme condition testing*. The simulation results with different inputs demonstrates that all members with those initial skill levels are passive and the value of population interaction graph in time shows a plateau equal to 0% activity throughout the simulation horizon.

3- *Consistency of output* by doing several replications can be used to assess the internal validity with acceptable range of variability in the results.

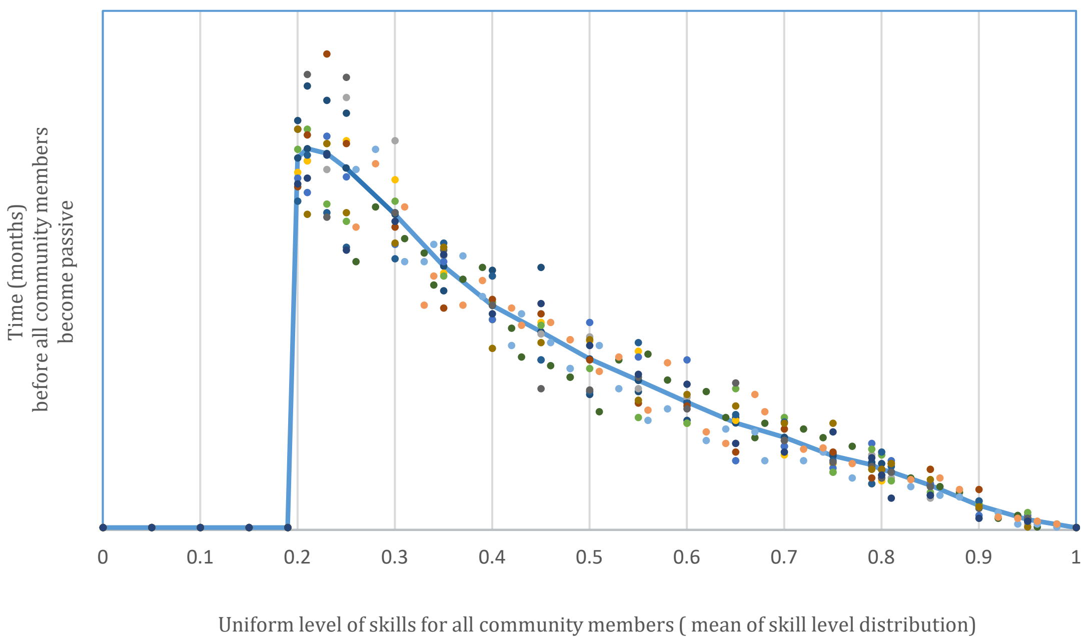


Figure 4-5: Model outcomes, which is used for operational validation skill for a community with 15 members interacting on 10 number of skills

4- The mean value of skill levels for all community members between 0.2 and 1 provide an appropriate interval to explain the *degenerate testing*. It depicts that by increasing the mean of skill levels the average lifespan of the community decreases non-linearly, which clearly supports the theory of the model.

5- The relationship between system's inputs and outputs after numerous experiments shows logical coherency and relevancy in general behavior of the conceptual model that can shows having *face validity* since it responds to the research questions.

4.5.3 Stability of outcomes

To create the Fab Lab environment, we defined several independent variables in order to reproduce attributes and behaviors of the actors. Since at the beginning of each simulation run, we assigned random initial values to these parameters, it was expected that there would not be fixed similar results throughout similar experiments. Therefore, we needed to repeat all of experiments for at least a certain number of time to obtain results convergence. This minimum number of replications helped us to have reliable average values.

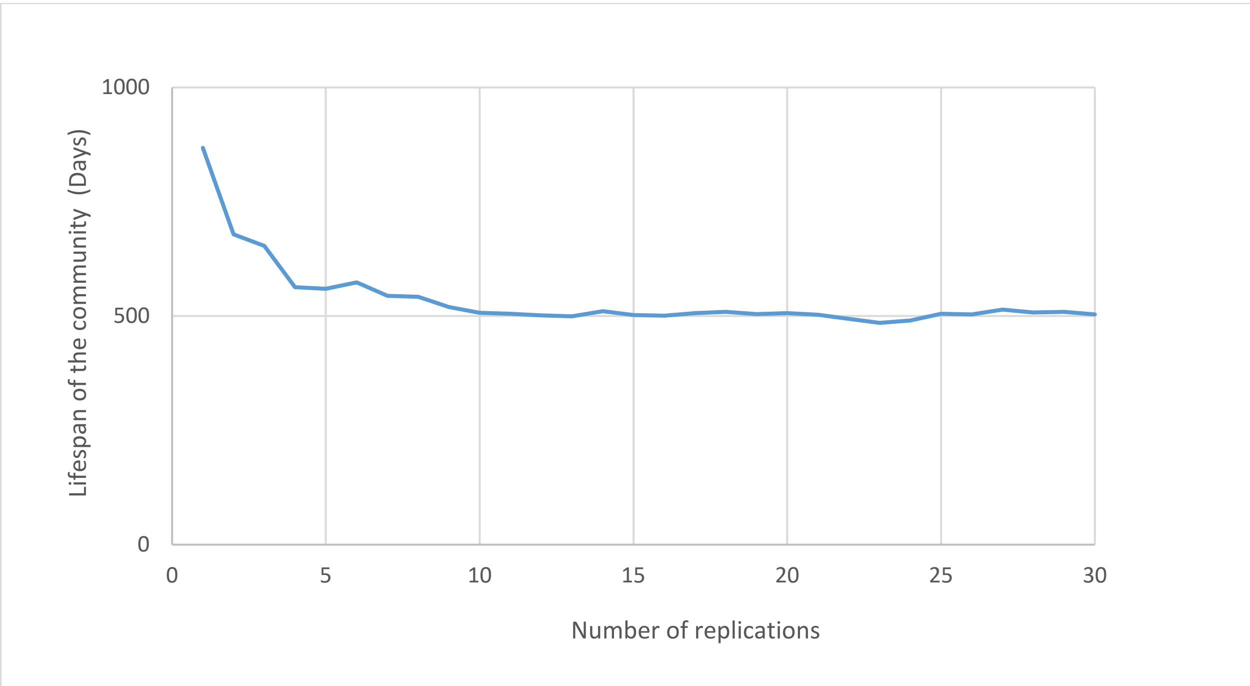


Figure 4-6: Convergence results for the lifespan of the community per number of replications.

The stability of the model was investigated for a community with 15 members in which actors are involved with 10 skills. Given that the average skill levels for all members are equal to 0.7, the averages of outputs from different replications are calculated. The results show that the value of community lifespan is stable after only 10 replications (Figure 4-6), and the value of community activeness converges after 6 replications (Figure 4-7). Consequently, based on this stability analysis, all of the presented outputs in this research were obtained from the average of outcomes derived out of 10 replications to guarantee authentic and consistent outputs.

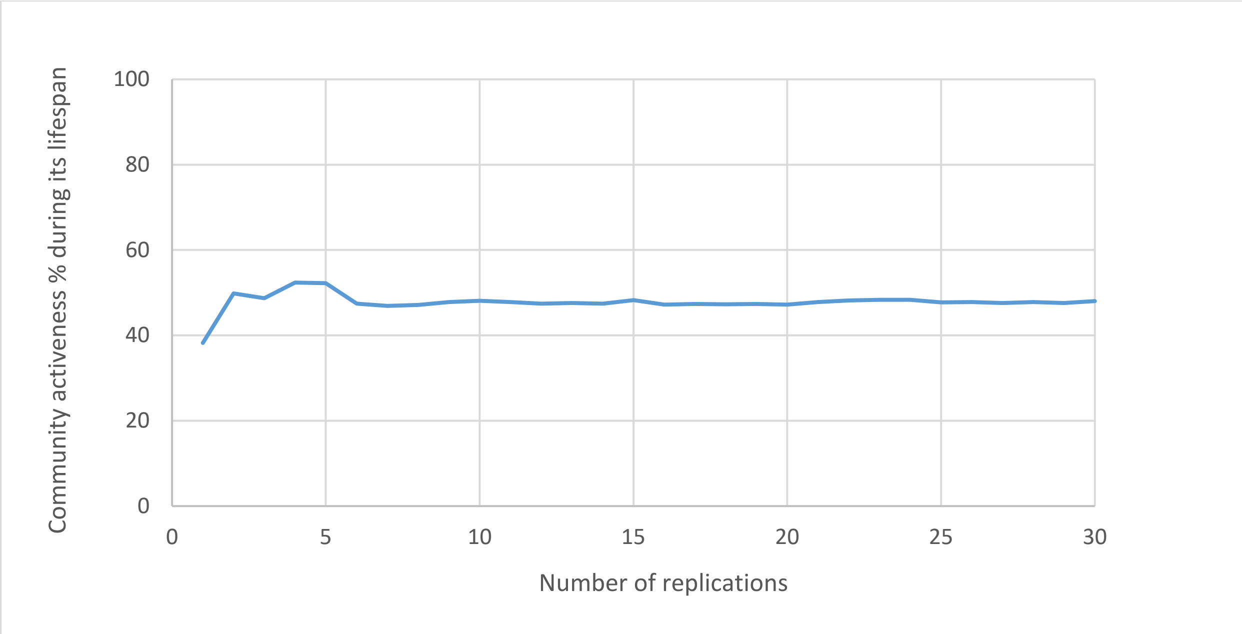


Figure 4-7: Stable results for community activeness throughout repeated similar experiments

4.5.4 Validation experiments

In the next chapter, we explain three series of experiments in which the first two series are planned to complete the validation process of this model in more depth. We discuss about the experiments' conditions, setups, and results. In the first experiments, we study the impact of different initial skill levels of members as the inputs on the active lifespan, level of activeness, and transferred skill/ knowledge in a community. Then for the next series of experiments, we review the impact of *communication accessibility* on group working, as explained in section 3.2.3.

CHAPTER 5 EXPERIMENTS

The simulation of the model proposed in the previous chapter provides the opportunity to experiment Fab Lab communities virtually with various setups and different condition scenarios. In this research, three series of experiments were carried to review the behavior of the system with different inputs including initial skill levels of members, communication accessibility, and motivation programs. This chapter presents the general conditions, specific assumptions, and plans of the experiments prior to the details results. Finally, we analyze and discuss these results.

5.1 General conditions

Having a flexible model to reproduce different kinds of Fab Lab environment, this simulation is programmed in a way to accept different inputs in the forms of initial values. There are two types of input to set up this model before simulation runs. The first group contains independent parameters, which only need an initial value, such as the community population, number of skills, or communication accessibility. On the other hand, the second group contains dependent variables with initial values that can change through interactions, like the skill levels of each member, or their expectation for each skill. To assign these initial values and parameters, we used normal distribution to create the environment of the community. Since we could not do endless number of experiments to cover all possible input options, we defined our community with fixed general conditions for all of our experiments (Table 5-1 and Table 5-2).

Table 5-1: Initial values of the parameters for all experiments.

Parameters		Series of experiments		
Symbol	Description	1st	2nd	3rd
N	Community population ($n \in N$)	15	30	10
M	Number of skills ($m \in M$)	10	10	10
Ca	Communication accessibility	100%	Various	100%
Minvert	Min required ΔE_{ij} for a proper communication	0.3	0.3	0.3
Maxvert	Max acceptable ΔE_{ij} for a proper communication	0.5	0.5	0.5
Tmp	Threshold to start motivation programs	N/A	N/A	Various
Imp	Intensity of the motivation programs	N/A	N/A	Various

Table 5-2: Initial range of values for sets of variables or parameters in each experiment.

Symbol	Description	Parameter	Range of parameters for each series of experiments		
			1st	2nd	3rd
$S_{nm}^{t=0}$	Initial levels of skill $m \in M$ of member $n \in N$	μ [1]	Various	0.6	0.9
		σ [2]	Various	0.2	0
I_n	Level of interest to participate in community activities of member $n \in N$	μ	1	1	1
		σ	0	0	0
X_{nm}	Expectation of member $n \in N$ for skill $m \in M$	μ	0.75	0.75	0.75
		σ	0.2	0.2	0.2
Y_n	Technology talent levels of member $n \in N$	μ	0.5	0.5	0.5
		σ	0.2	0.2	0.2
D_n	Diligence levels of member $n \in N$	μ	0.5	0.5	0.5
		σ	0.2	0.2	0.2
E_n	Extroversion levels of member $n \in N$	μ	0.5	0.5	0.5
		σ	0.2	0.2	0.2
F_m	Levels of easiness of skill $m \in M$	μ	0.5	0.5	0.5
		σ	0.25	0.25	0.25
MCA_{pm}	Minimum collective agreement of group p to interact for skill m	μ	0.66	0.66	0.66
		σ	0.1	0.1	0.1
Ei	Increment of interest ΔX that can be increased by motivation program	μ	N/A	N/A	0.05
		σ	N/A	N/A	0

Thus, we created a normally distributed Fab Lab community for all of our experiments by choosing general initial values (the identification of realistic values for these parameters is outside the scope of this research and would be a project in itself). For example, for some parameters, which address to the personality of members, we assumed that the studied community comprises people's

[1] The mean of the normal distribution function

[2] The standard deviation of the normal distribution function

personalities with normal distribution having an average midpoint value ($\mu = 0.5$) for their technology talent, diligence level and extroversion statuses. Moreover, since we did not aim to study the impact of these parameters, we chose the values for the related standard deviations equal to 0.25 in order to have only an acceptable diversity with no particular conditions. Likewise, the distribution of the skills in terms of easiness are assumed similarly with $\mu = 0.5$ and $\sigma = 0.25$.

Similarly, for the interest level of members to participate in the Fab Lab activities, we assumed in all of experiments that members are 100% interested to participate; however, we recommend for future studies that some experiments should have different interest distributions.

The minimum collective agreement is another parameter that needs initial values. We assumed that if only two out of three members in a group agree for an activity, then the group does that action collectively. Moreover, we chose a standard deviation $\sigma = 0.1$ that can offer various values.

According to Table 3-1, there are several tools, equipment, and facilities in a Fab Lab community that members first need to learn how to work with them. Thus, the initial value of M=10 skills seems acceptable. In addition, the distribution of X_{nm} with $\mu = 0.75$ and $\sigma = 0.25$ explains that the average self-expectation of the community's members is to learn skills in a way that they can be involved and practice individually. However, they may have specific favorite or preferable skills.

Based on what we discussed in section 3.2.3 and 4.3.1, the similarity factor ($| \Delta E_{ij} |$) must be within an acceptable range to establish a connection between two agents. Researches show that for a proper communication, people need a dissimilarity in extroversion level, although this difference should not be too much (Thorne, 1987). For that reason, we defined a minimum dissimilarity equal to 0.3 and a maximum dissimilarity equal to 0.5. This interval can be larger or narrower to make more or less connections possible respectively. Since the impact of this parameter on Fab Lab interactions is not studied in this research, we chose a normal range based on non-peer reviewed internet pages and forums. Nevertheless, the impact of extroversion level of community members, or any other psychological factor, must be studied, it can be used in future research.

5.2 Design of experiments

In this research, there are two main objectives to conduct experiments. First, we need to evaluate the validity of our proposed model in more detail since there were no previous or similar researches in this field. Thus, the first group of experiments consists of two series of simulation experiences to investigate the performance and validity of this model. Next, the second experiment consists of one series of simulation experience to assess the possibility of improving the productivity of a community using motivation programs. This section explains the experiment plan for each series.

5.2.1 First series of experiments: the impact of skill levels

This series of experiments is the sensitivity analysis of the initial skill levels of members to study its impacts on the following indicators (Table 5-3).

- The active lifespan of the community;
- The level of activeness (average percentage of active members at lifespan θ);
- Transferred skill/knowledge of a community;

Table 5-3: Experiment plan to study the impact of skill levels.

Initial skill levels	Standard deviation	
Mean	σ = 0	σ = 0.1
0.3	10 replications	10 replications
0.5	10 replications	10 replications
0.7	10 replications	10 replications
0.9	10 replications	10 replications

As explained before, this series of experiments is conducted to validate the simulation functionality. The reason to select these indicators is to study the impact of different initial skill levels on the basic behaviors of the communities, which are activities and interactions. A community is considered alive and active as long as it has interacting members. The activeness of a community can be assessed by measuring the average percentage of active members or the lifespan of a community. Next, the transferred skill represents the output of the productive interactions of a community. In all experiments of this series, the community consists of 15 members who interacts over 10 skills (Table 5-1). It is assumed that there is no diversity in terms of interest levels of members to participate (Table 5-2). In other words, members have homogeneous levels of interest.

5.2.2 Second series of experiments: the impact of communication accessibility

Normally, a community facilitates the connectivity of its members depending on how it provides the accessibility opportunities. For instance, we can expect more group working in a community that has an active page in a social media or has regular general meetings to connect its members. Regardless how a community works to develop connections, these experiments investigate the impact of accessibility opportunities on individual involvement or group working in order to validate the outcomes of our proposed model.

Besides, we also study how the community level of openness can make the interested members passive. To set up the openness and accessibility, the community is divided in divisions. When the number of division is one, it means all members have access to each other with 100% of accessibility, whereas in 0% of openness, members do not have any access to each other and they can only work individually (i.e., each member is in its own division). Therefore, in these experiments we planned to study the impact of communication accessibility (*Ca*) on the following indicators respecting the general conditions of the experiments (Table 5-1 and Table 5-2).

- Individual involvement
- Interacting in groups
- Passive members

More specifically, we evaluated Fab Lab communities with four levels of openness and with 30 members, while interacting over 10 skills (Table 5-4).

Table 5-4: Experiment plan to study the impact of parameter *Ca* (community accessibility)

<table>
<tr><td></td><td></td><td>Size of community</td></tr>
<tr><td></td><td></td><td>30</td></tr>
<tr><td rowspan="4">Communication accessibility</td><td>Ca = 0 %</td><td>10 replications</td></tr>
<tr><td>4 sub groups (25%)</td><td>10 replications</td></tr>
<tr><td>2 sub groups (50%)</td><td>10 replications</td></tr>
<tr><td>Ca = 100 %</td><td>10 replications</td></tr>
</table>

5.2.3 Third series of experiments: the impact of motivation programs

When all members in a community become passive, the community itself is inoperative. As a result, it is up to the Fab Lab managers to extend the community lifespan by motivating its members to interact or by absorbing new members. The cost of the promotions to keep members interested is usually critical and having a community with a longer active life needs more investment and acceptable rate of return. For that reason, this third series of experiments was conducted to study the impact of any motivation programs on community members as a managerial tool. However, the types of motivation programs and their productivities are not in the scope of this research. Here, we are interested in two controllable factors including the trigger threshold and the intensity of motivation programs. The studied outputs represents the behavior of the community in terms of active lifespan, level of activeness, transferred skill/knowledge, and cost of motivation programs, provided that the efficiency and the effectiveness of these motivation programs are 100%. In other words, it is assumed that, as long as the value of members' expectation level does not exceed one, each motivation program increases the expectation level of members who participated on that motivation program by a value equal to 0.05. This increase in expectation level is applied for all of the skills uniformly. For this series of experiments, we study a community with 10 members whose members are interacting for 10 skills. Moreover, the population has 100% communication accessibility (i.e., all members within one division) to find their connections (Table 5-1 and Table 5-2). Finally, the experiment scenarios were arranged according to Table 5-5 to study the impact of different intensity and threshold in motivation programs.

Table 5-5: Experiment plan to study the impact of intensity and threshold in motivation programs

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="3">Intensity</td></tr>
<tr><td colspan="3">Motivated % from passive population</td></tr>
<tr><td>20%</td><td>50%</td><td>100%</td></tr>
<tr><td rowspan="2">Threshold</td><td rowspan="2">Passive % of community population</td><td>50 %</td><td>10 replications</td><td>10 replications</td><td>10 replications</td></tr>
<tr><td>80 %</td><td>10 replications</td><td>10 replications</td><td>10 replications</td></tr>
</table>

5.3 Performance indicators

Before detailing the experiments and the results, we clarify in this section the specific performance indicators we used. To do so, we defined functions and events in the AnyLogic platform, and then we used them in simple algorithms. Nonetheless, in this section, we do not explain the related java coding. We only try to explain the KPIs using mathematical formulation.

The first performance indicator is the *Active lifespan* of the community. It presents whether there are any active member exists in the community or not. To calculate the value for this indicator, we measured the percentage of passive members every 2 weeks (14 simulated days). When the value of passive members reached to 100% and is steady, we considered that time as the end of the active life of the community.

Cps^t	Community passiveness percentage at simulation time *t*;
B_n	Indicator that shows whether agent *n* is passive or not;
A_n	Indicator that shows whether agent *n* is active or not;
Cac^t	Community activeness percentage at the simulation run time *t*;
θ	Lifespan of the Fab Lab community when $Cps^t = 100$ % for 30 continuous days

$$B_n = \begin{cases} 1 & (\forall\, m \in M, \forall\, p \in P, \forall\, n \in p \mid SI_{nm} = 0) \lor \\ & (\forall\, m \in M, \forall\, p \in P, \forall\, n \in N, \forall\, t \in T \mid n \notin p \land S_{nm}^{t} \leq 0.2) \\ 0 & Otherwise \end{cases} \tag{5-1}$$

$$Cps^t = 100 \times \sum_{n=1}^{N} B_n / N = 100 - Cac^t \tag{5-2}$$

$$A_n = 1 - B_n \tag{5-3}$$

$$Cac^t = 100 \times \sum_{n=1}^{N} A_n / N = 100 - Cps^t \tag{5-4}$$

Now that we know the community activeness at time *t* and the lifespan of the Fab Lab community, we can calculate the average activeness of the community, which we call *level of activeness* (*Aac*) during its lifespan according to the following formula. This indicator shows the average percentage of the community who interacts during its lifespan.

$$Aac = \frac{1}{\theta} \int_{t=0}^{\theta} Cac^t \, dt \tag{5-5}$$

The third performance indicator is the transferred skill/knowledge through interactions. We assume that for *n* members of a community with 0 skill level for *m* skills, their opportunity to improve their skill levels to reach maximum value (i.e., 1) is equal to $n \times m$. We call this total progression as the transferred skill since the improvement happened through the interactions within the community with no support by any external source.

Tts^t Total transferred skill of the community during at simulation time *t*;

Ats Average percentage of the transferred skill of the community during its lifespan θ;

$$Tts^t = \sum_{m=1}^{M} \sum_{n=1}^{N} S_{nm}^{t} - \sum_{m=1}^{M} \sum_{n=1}^{N} S_{nm}^{t=0} \quad (5\text{-}6)$$

$$Ats = \frac{1}{\theta} \int_{t=0}^{\theta} \frac{Tts^t}{m \times n} \, dt \quad (5\text{-}7)$$

For example, Figure 5-1 depicts the transferred skill or knowledge through interactions of a community with 15 members involving 10 skills. A comparison between three different initial skill levels demonstrates that with a similar interest to participate in the community and identical expectation to improve their skill levels, the transferred skill in a community with lower initial skills are higher than a community with members with higher initial skill levels.

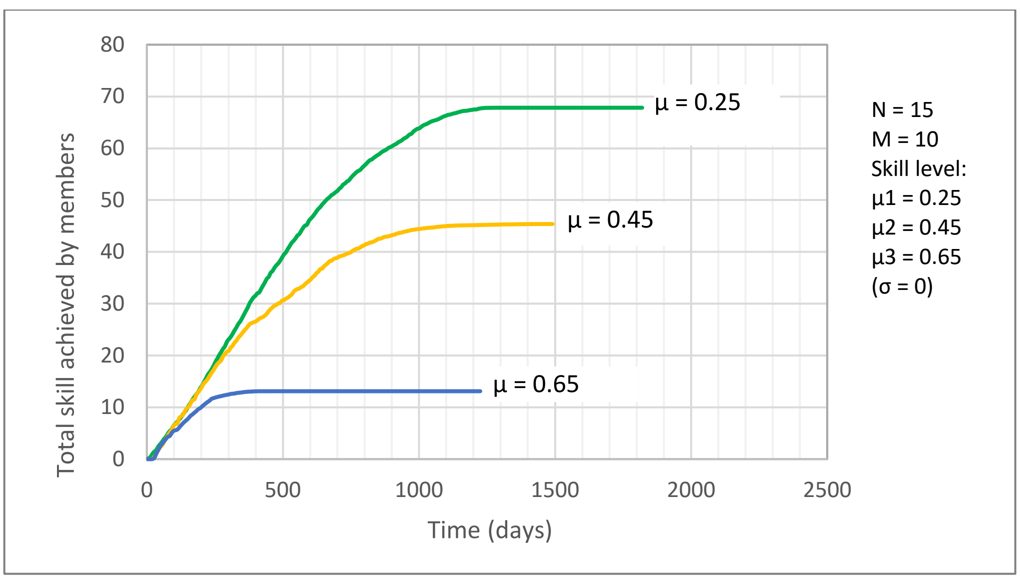


Figure 5-1: Transferred skill for a community with 15 members and 10 number of skills.

There are also two other indicators, which display whether an agent is involved in the community as an individual member or a group member, and interacts with its groupmates provided that the agent is not passive.

Inv_n^t Individual involvement status of agent *n* at simulation time *t*;

Pin^t Percentage of community population that works individually at simulation time *t*;

Grp_n^t Group working status of agent *n* at simulation time *t*;

Pgr^t Percentage of population that interact in groups at simulation run time *t*;

$$Inv_n^t = \begin{cases} 1 & if \quad (\forall\, p \in P, \forall n \in N|\; n \notin\; p\; \wedge B_n = 0) \\ 0 & \quad\quad\quad\quad\quad\quad\quad\quad Otherwise \end{cases} \tag{5-8}$$

$$Pin^t = 100 \times \sum_{n=1}^{N} \frac{Inv_n^t}{N} \tag{5-9}$$

$$Grp_n^t = \begin{cases} 1 & if \quad (\forall\, p \in P, \forall n \in N|\; n \in\; p\; \wedge B_n = 0) \\ 0 & \quad\quad\quad\quad\quad\quad\quad\quad otherwise \end{cases} \tag{5-10}$$

$$Pgr^t = 100 \times \sum_{n=1}^{N} \frac{Grp_n^t}{N} \tag{5-11}$$

Now, we can calculate the average active population who is involved in the group activities during the community lifespan (*Agr*), and the average active population who is involved individually during the community lifespan (*Ain*).

$$Ain = \frac{1}{\theta} \int_{t=0}^{\theta} Pin^t\, dt \tag{5-12}$$

$$Agr = \frac{1}{\theta} \int_{t=0}^{\theta} Pgr^t\, dt \tag{5-13}$$

The last performance indicator addresses the cost of motivation programs. By motivation programs, we mean any kinds of activity, which can motivate members to participate in the community interactions by increasing levels of self-expectation. Actual examples of these programs includes presentations and demonstrations of new technologies, workshop, seminar, or any other similar activities. The specifics of these motivation programs are not in the scope of this project. Each Fab Lab manager can organize different types of program depending on their budget or marketing plan with different efficiencies. In this research, only the repetition of these programs is important. Therefore the number of members who need to be motivated to increase the lifespan of the community is considered as the motivation cost indicator ($Mcost$). We assumed that the productivity of all motivation programs is 100% regardless of their types and details.

Then, when $Cps^t \geq Tmp \times 100$, a motivation program is initiated. Its impact is calculated as $Nmt^t = Imp \times Cps^T$, with a cost of $Mcost = \sum_{t=0}^{\theta} Nmt^t$, with:

Cps^t Community passiveness percentage at time t;

Tmp Threshold of motivation programs, which is the limit of percentage of passive members in the community to start the motivation program;

Nmt^t Number of members who are motivated in each motivation programs;

Imp Intensity of motivation programs, which shows the percentage of passive members who are reactivated in the motivation program;

Provided that $(Cps^t \neq Cps^{t-1}) \wedge (\exists\, n \in N\colon\ B_n^t = 1 \Rightarrow B_n^{t-1} \neq 1)$

5.4 Model qualitative validation

This section presents the results of the first two series of experiments (respectively impacts of initial skill level and communication accessibility) aiming at qualitatively validating the general dynamics of the proposed model.

5.4.1 Impact of initial skill levels

The first series of experiments studies the impact of skill levels on the community behavior. Considering the general configuration of all experiments from Table 5-1 and Table 5-2, we conducted experiments in accordance with what is designed in section 5.2.1 to review the impact of different skill levels in a community with 15 members.

In order to study the impact of skill levels, we first review the system behavior according to various means of initial skill level distribution (μ). Results show that the interactions of a community consisting of members with higher skill levels stop being active sooner. In other words, the communities with members with lower initial skill levels remain active for longer period. For example, Figure 5-2 shows that a community which all of members have a uniformly distributed (σ = 0) initial skill levels equal to 0.5 has a lifespan equal to 37.6 months, whereas a similar community but with initial skill levels equal to 0.9 has 12 months active lifespan. Besides reviewing skill improvement, the total transferred skill in the community (Tts^t) with initial skill levels equal to 0.3 is much higher than a community with a distributed initial skill levels with μ = 0.7 and σ = 0 (Figure 5-3).

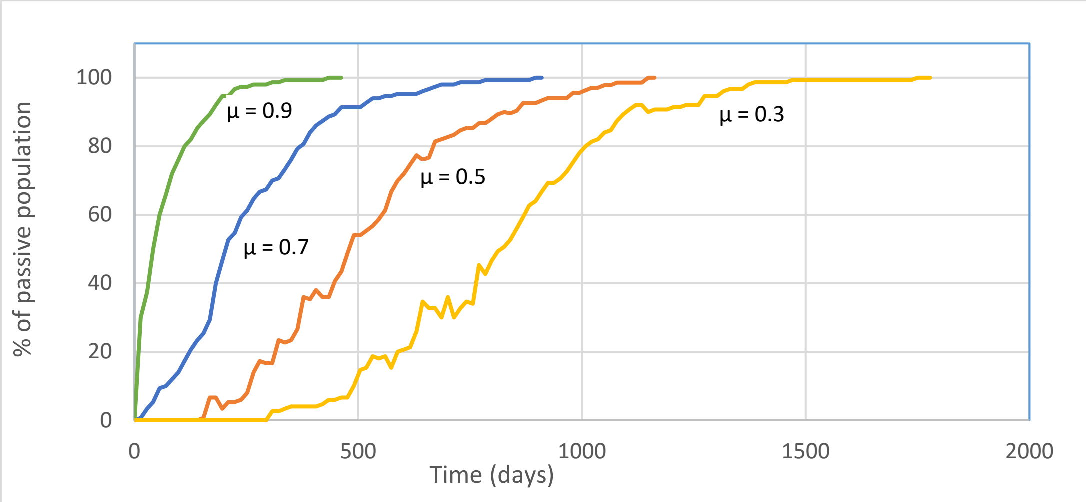


Figure 5-2: Passive population percentage (Cps^t) of a community, configured according to the 1st series of experiments for 4 different initial skill levels, with σ = 0.

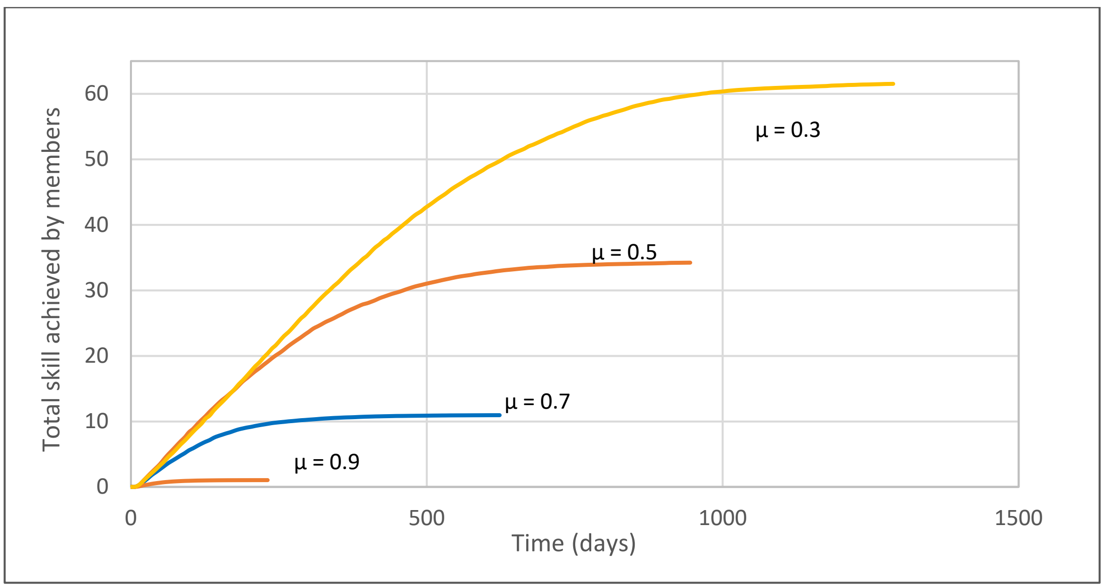


Figure 5-3: Skill level improvement (Tts^t) of a community, configured according to the 1st series of experiments for 4 different initial skill levels, with σ = 0.

The second important parameter to study the impact of initial skill levels is the diversity of skill levels or the standard deviation of initial skill levels distribution (σ). Results show that a more diverse initial skill levels tends to increase the lifespan of the community. In other words, diverse initial skill levels tend to postpone the state of 100% passiveness. As presented in Figure 5-4, passive population curves are below when the initial skill levels has a higher standard deviation (σ=0.1). That means that the diversity in initial skill levels increases the active lifespan to the community. Figure 5-5 depicts the impact of the mean value and standard deviation of the distribution of initial skill levels simultaneously.

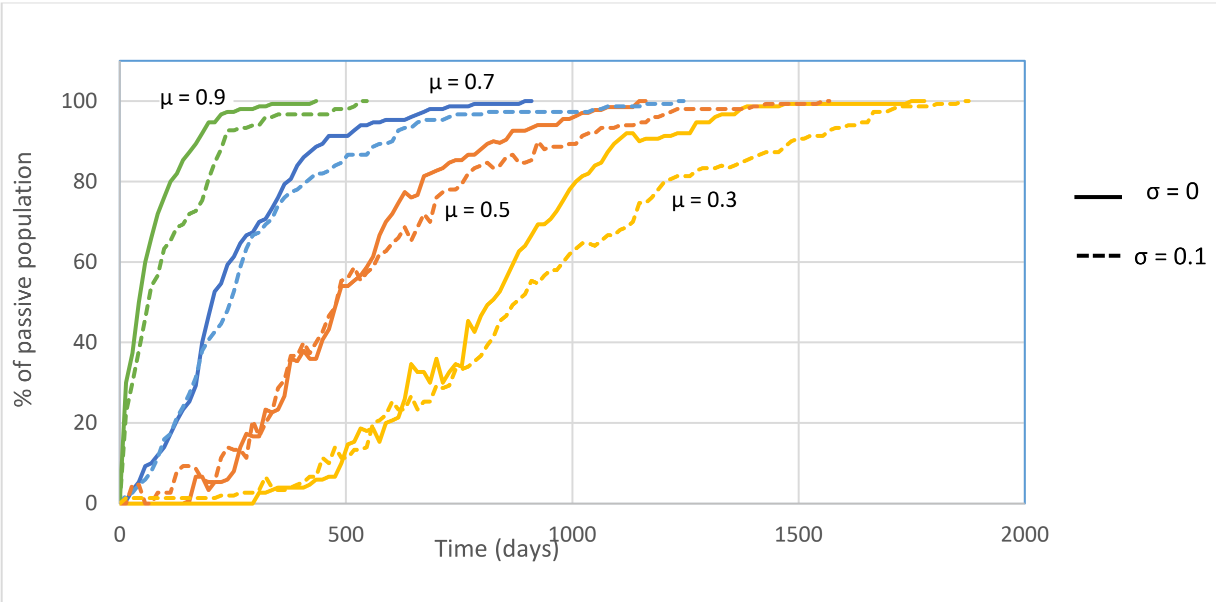


Figure 5-4: Passive population percentage (Cps^t) of a community, configured according to the 1st series of experiments for 4 different initial skill levels, with σ = 0 and σ = 0.1

The results of the first series of experiments also show the impact of skill levels on two other performance indicators. For instance, a community with higher initial skill levels has a lower average of activeness. That means that the average number of members who are active and interact during the lifespan of a community with higher initial skill levels is less than the activeness level (*Aac*) of a community with lower initial skill levels. Moreover, the diversity of skill levels has a negative effect, which means that having different skill levels will result in lower levels of activeness (Figure 5-6).

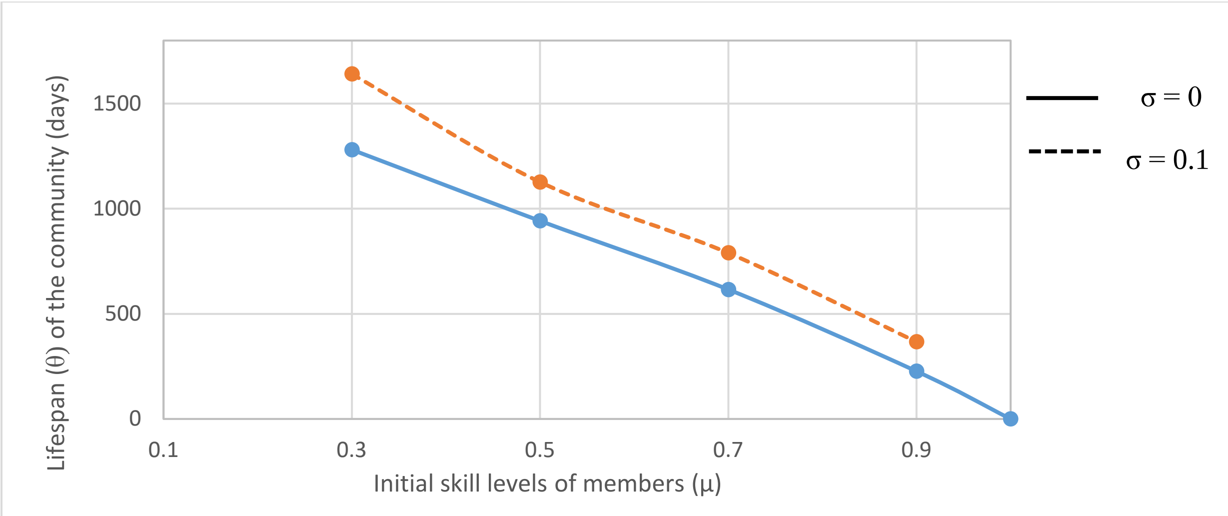


Figure 5-5: Comparison of lifespans (θ) for a community, configured according to the 1st series of experiments for 4 different initial skill levels and 2 standard deviations.

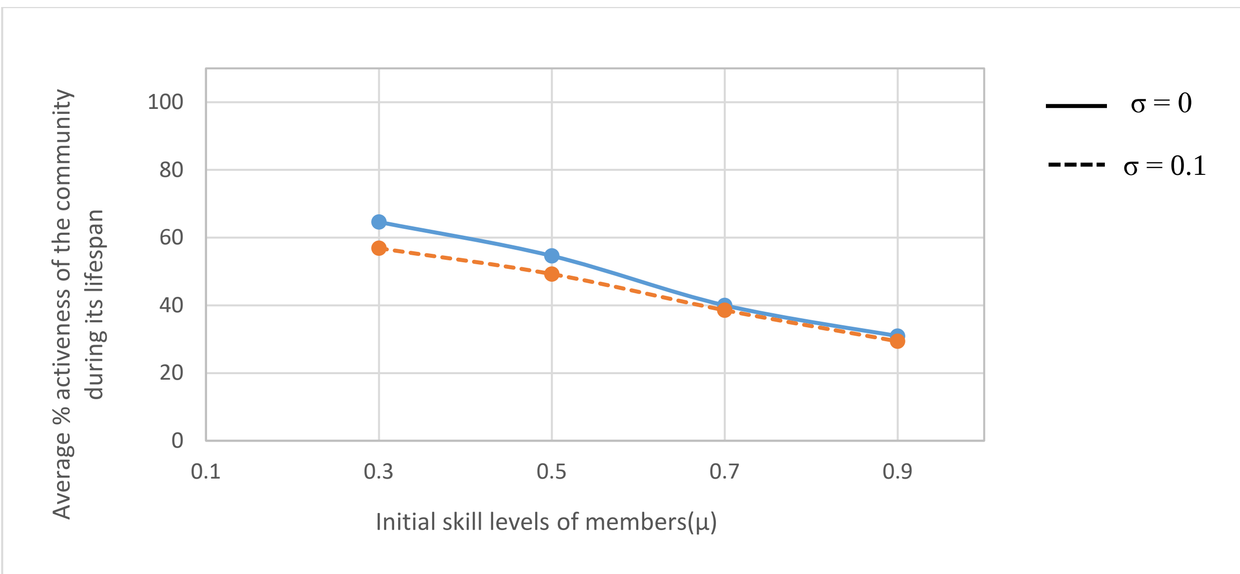


Figure 5-6: Comparison between two averages of activeness (Aac) during the lifespan of a community, configured according to the 1st series of experiments for 4 different initial skill levels and 2 standard deviations.

Likewise, initial skill levels have similar impact on average transferred skill (*Ats*) during a community lifespan. The total transferred skill or knowledge in a community with more skillful members is less than a community with lower skill levels. However, skill level diversity on skill improvement has the opposite effect (Figure 5-7). That means the diversity in skill levels of the community members' results in more skill improvement through interactions.

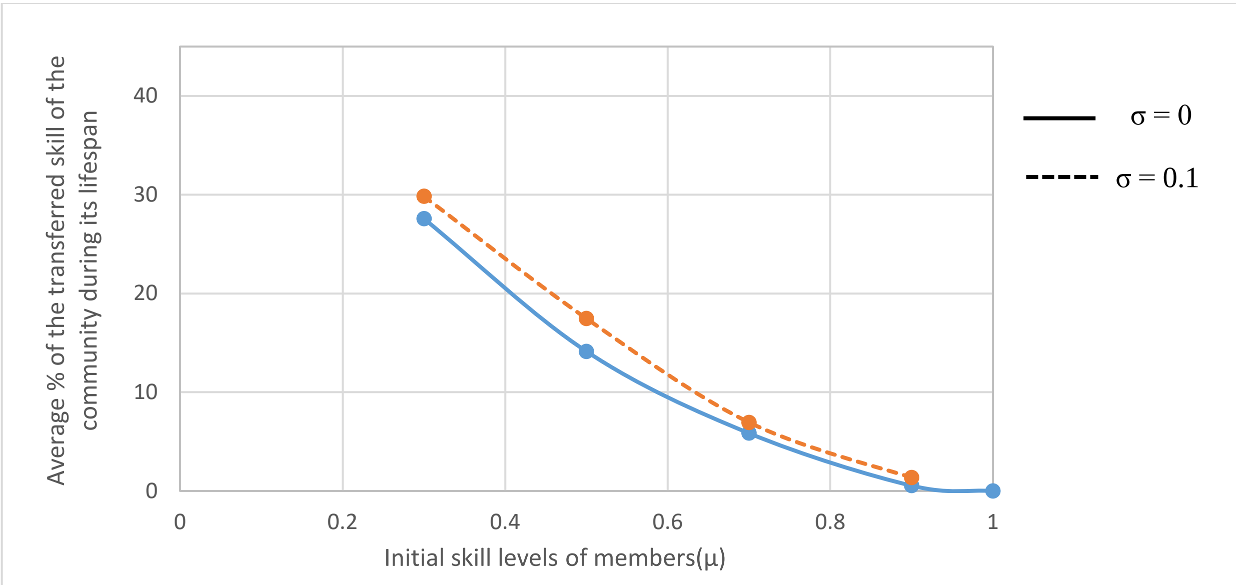


Figure 5-7: Comparison of average progression in skill levels (Ats) during the lifespan of a community, configured according to the 1st series of experiments for 4 different initial skill levels and 2 standard deviations.

5.4.2 Impact of communication accessibility

The second series of experiments studies the impact of the community level of openness. It assesses how accessibility opportunities (*Ca*) affects the involvement and group working of members in a community. Hence, we conducted a series of experiments according to what we designed in section 5.2.2 regarding the general configuration of all experiments from Table 5-1 and Table 5-2 in order to study the impact of four different values of accessibility opportunity (*Ca*) in a community with 30 members.

Results show that by increasing the accessibility of communication, the percentage of the population who interacts in groups increases (Figure 5-8). Obviously, the percentage of group working members (Pgr^t) is not steady during the community lifespan. Similarly, it also decreases in time, except when the value of *Ca* is equal to zero and there is no group. In that case, members can only be involved in the community as individuals. In other words, as shown in Figure 5-9, increasing the communication accessibility (Ca) caused noticeable decrease in the percentage of active individual members (Pin^t).

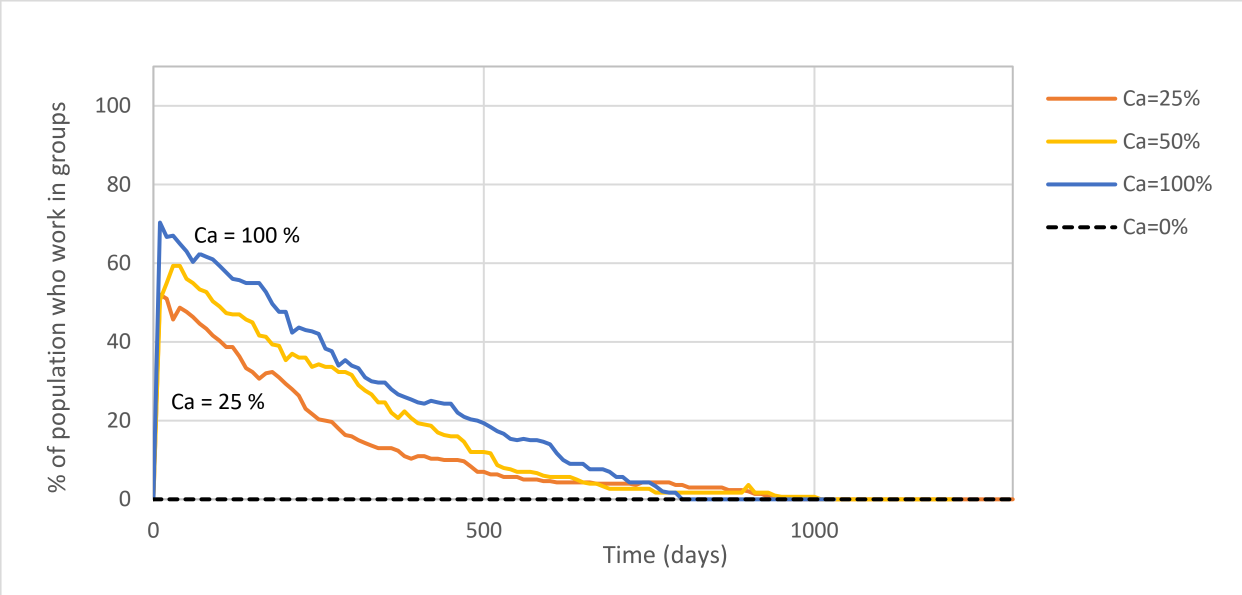


Figure 5-8: Percentage of the community with 30 members who work in groups (Pgr^t) during its lifespan.

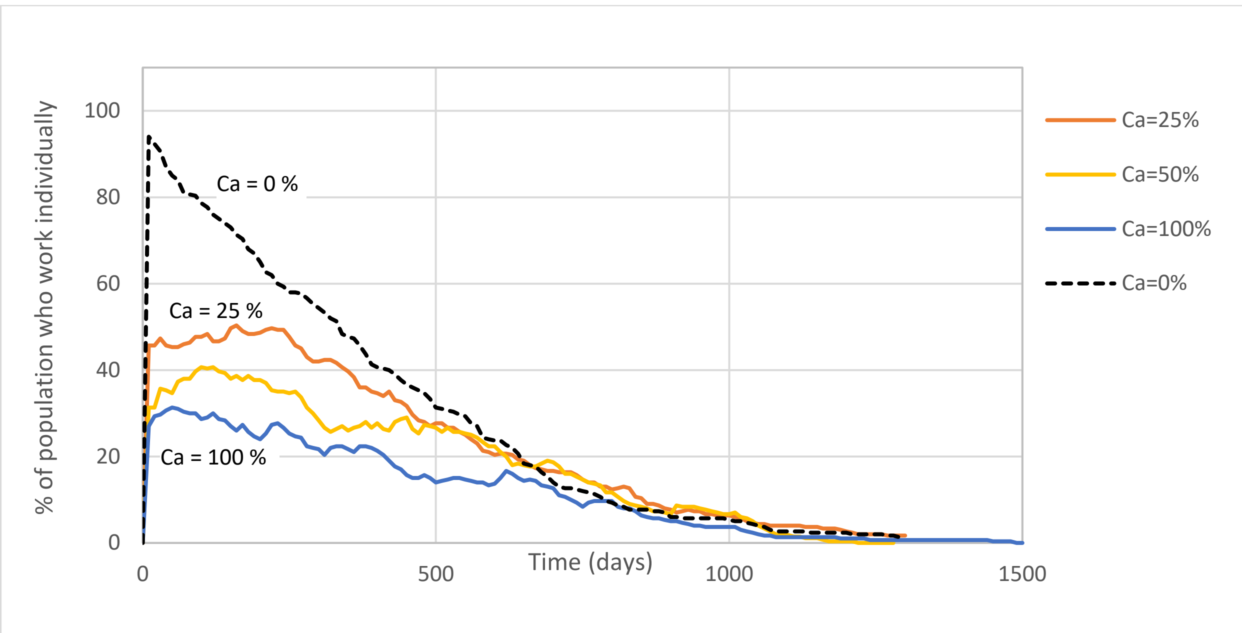


Figure 5-9: Percentage of the community with 30 members who work individually during its lifespan (Pin^t).

Results also show that the passive population percentage (Cps^t) did not experience considerable changes in different communication accessibilities (*Ca*) except in *Ca* equal to 0 (Figure 5-10). However, a very slight decline in lifespan (θ) and a small increase in level of activeness is observed in higher communication accessibilities (Figure 5-11).

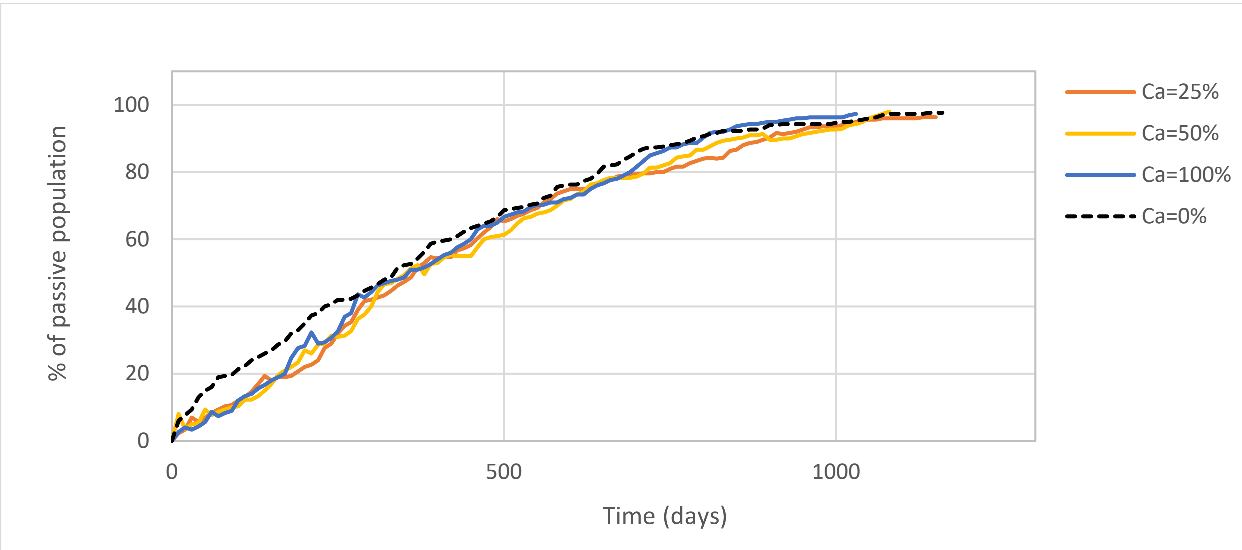


Figure 5-10: Passive population percentage (Cps^t) of a community with 30 members, configured for the 2nd series of experiments with 4 different communication accessibilities (*Ca*).

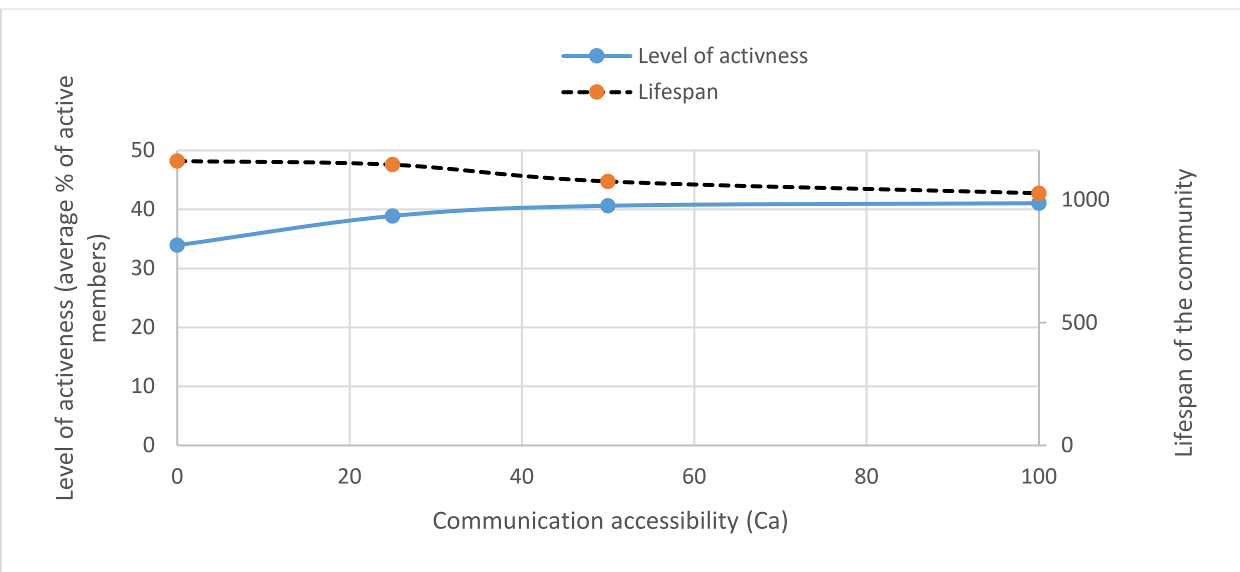


Figure 5-11: Level of activeness (*Aac*) and lifespan (θ) of a community with 30 members for 4 different communication accessibilities (*Ca*).

Figure 5-12 summarize the impact of communication accessibility (*Ca*) on team working in a community. It shows how the average team working during a community lifespan (*Agr*) increases for higher level of communication accessibilities, while having a lesser impact on individual involvement among members. As explained in Figure 5-8 the group population is zero for *Ca* = 0 and for each level of *C*a, the level of activeness is equal to sum of the individuals plus group populations.

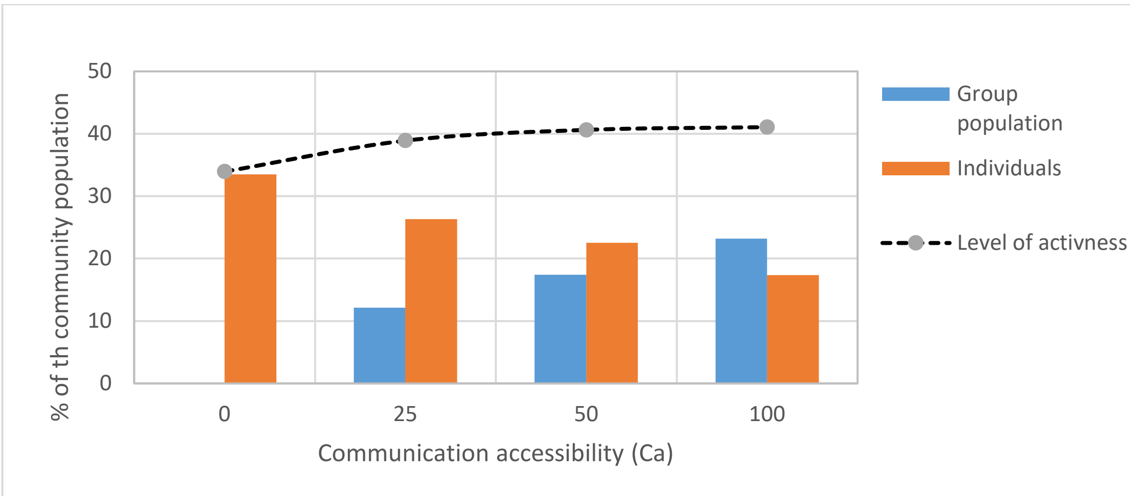


Figure 5-12: Active population who are interacting in a group (*Agr*) or involved individually (*Ain*) in a community with 4 different communication accessibilities (*Ca*).

5.4.3 Discussion

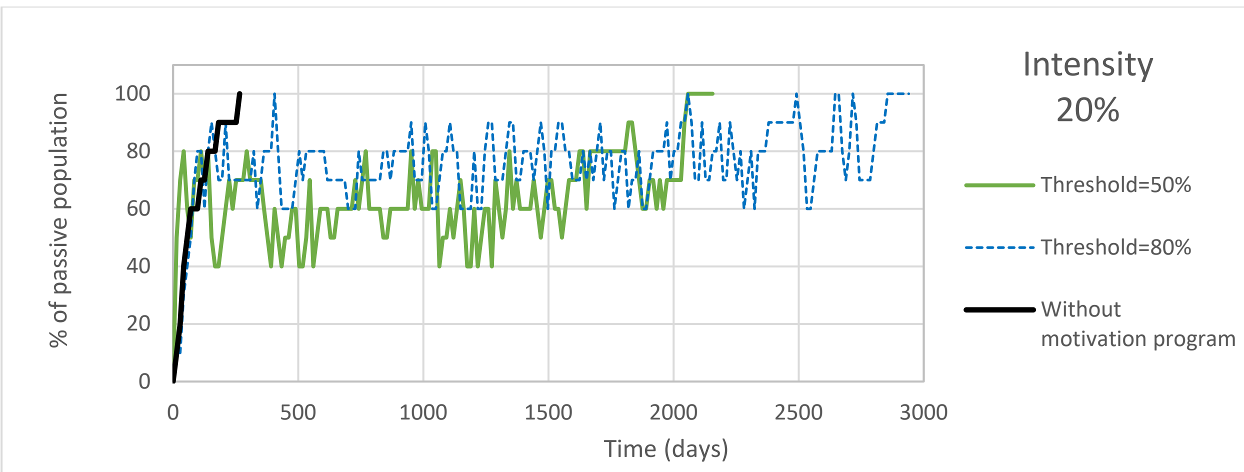
The experiments show that the higher initial skill level results to shorter active lifespan and lower total transferred skill, which gives a lower average of activeness. On the other hand, a diversity in initial skill levels increases the lifespan of the community and average transferred skill. Furthermore, they depict that group working is more probable in communities that facilitate communication and information sharing among their members.

These experiments support the validity of our model since the results from both series of experiments are consistent that can be expected from an actual Fab Lab. In this regard, future work must include data collection for detailed quantitative validation. However, it is not easy because actual Fab Lab have dynamic population with new members and members leaving the community constantly.

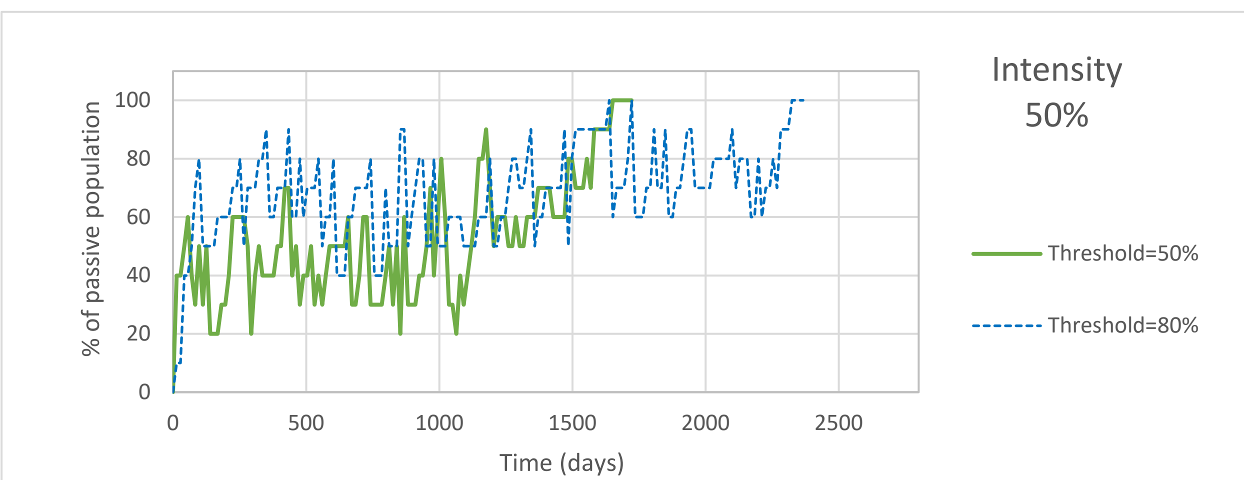
5.5 Impact of motivation programs

Finally, the last series of experiments studies the impact of motivation programs on the behavior of the communities. To study the impact of motivation programs, defined in terms of intensity (*Imp*) and threshold (*Tmp*), in a community with 10 members, we conducted a series of experiments according to the plan of experiment described in section 5.2.2 regarding the general set up presented in Table 5-1 and Table 5-2.

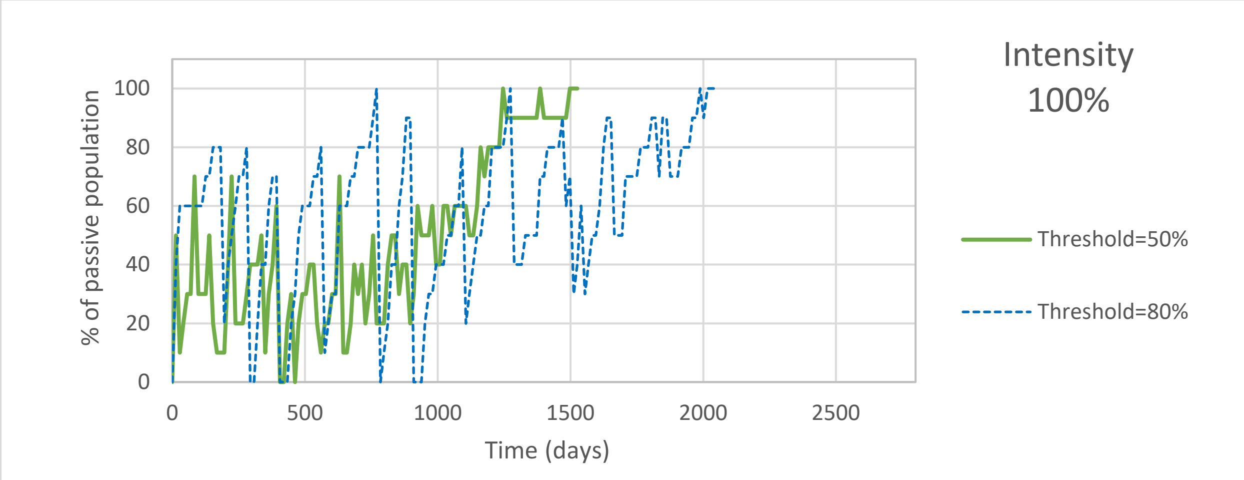
The first community behavior, which is influenced by motivation programs is the passive population percentage of a community (Cps^t) through members' interactions. Figure 5-13 (a) to (c) presents Cps^t in different conditions. These three instances of simulation show visually the capacity of various intensity and threshold to delay the increase in passivity of the population.



(a)



(b)



(c)

Figure 5-13 (a to c): Passive population percentage (Cps^t) of a community, configured according to the 3rd series of experiments for different motivation programs in terms of intensity (*Imp)* and threshold (*Tmp*).

In Figure 5-14, we can see the effect of having a motivation program. The initial skill levels of all members in a community with 10 members on 10 skills are 0.7 uniformly and the community lifespan is 580 days. Whereas, a motivation program with 50% threshold a 50% intensity keeps members interested and increases the lifespan to 2400 days.

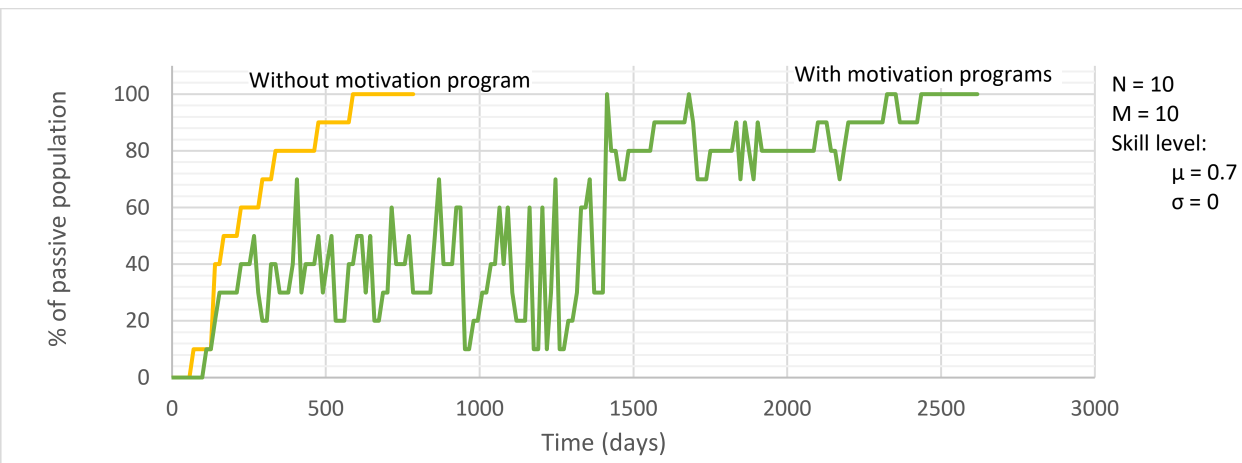


Figure 5-14: Example of Cps^t (passive population) for a community with 10 members in two conditions.

More specifically, results show that the level of activeness increases somewhat for more intense motivation programs. In addition, it shows that when the motivation programs start later (i.e., with higher threshold), the level of activeness of the community (*Aac*) decreases (Figure 5-15).

For example, a community that starts having motivation programs with 80% passive population, even if it has a 100% intense program, its level of activeness does not go higher than 42%. Whereas, the same community, which starts its motivation program sooner with lower threshold equal to 50% has 46% level of activeness only with a 50% intense program.

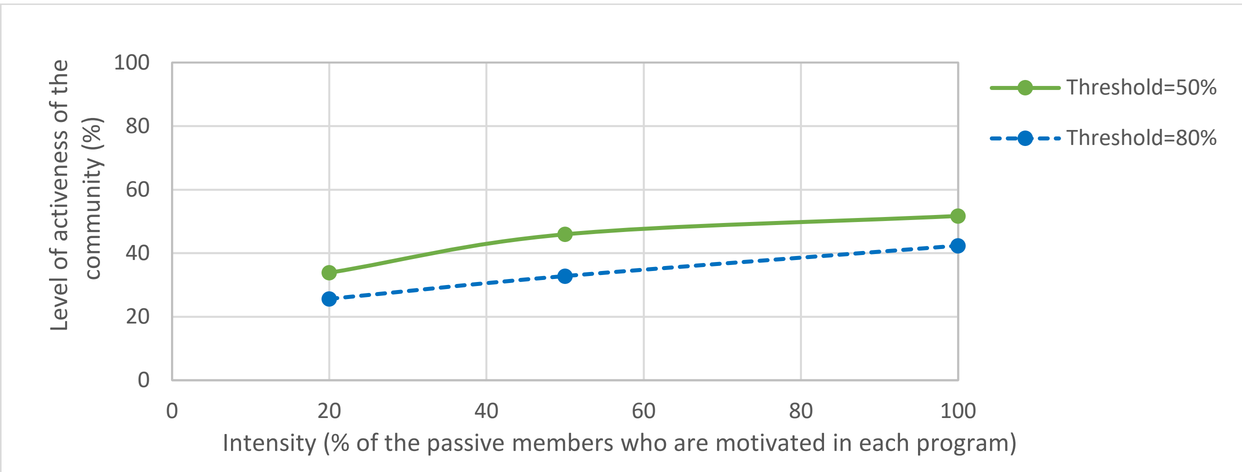


Figure 5-15: Averages of activeness (*Aac*) during the lifespan of a community, configured according to the 3rd series of experiments obtained in various values of intensity and threshold of motivation programs.

On the other hand, the lifespan (θ) decreases quite sharply for motivation programs with intensity value below 50%, and then continue to decline slightly. Unlike the level of activeness, motivation program with level of threshold equal to 80% causes a rise to the active lifespan of the community in comparison with threshold equal to 50%. As it is shown in Figure 5-16, a motivation program with 20% intensity for 50% threshold results in a longer lifespan than a program with 100% intensity, which started to motivate members in 80% level of threshold. That means the higher the intensity of the program, the shorter the lifespan and the higher the level of activeness. However, if we start to motivate a community with more passive members (i.e., higher threshold), Fab Lab managers need to have more intense programs in order to have the same result in comparison to lower threshold programs.

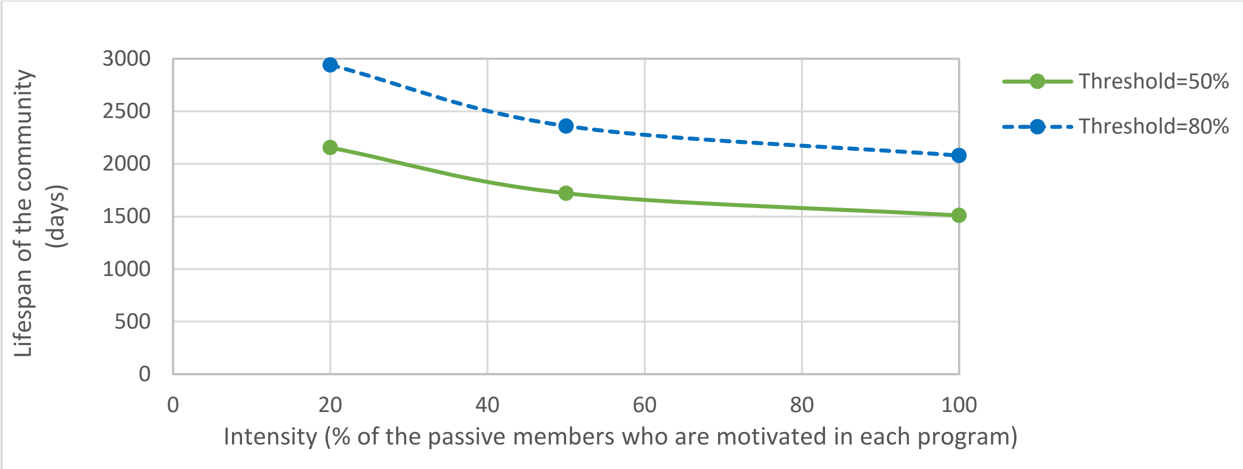


Figure 5-16: Comparison of lifespans (θ) for a community, configured according to the 3rd series of experiments with various values of intensity and threshold of motivation programs.

The next behavior of the community we studied is the skill transferred during community interactions. The related diagrams shows similar pattern for all motivation programs with different values of intensity and threshold (Figure 5-19). Accordingly, Figure 5-17 shows a small drop in average improvement in skill levels (*Ats*) for higher threshold and a minor increase for more intense programs.

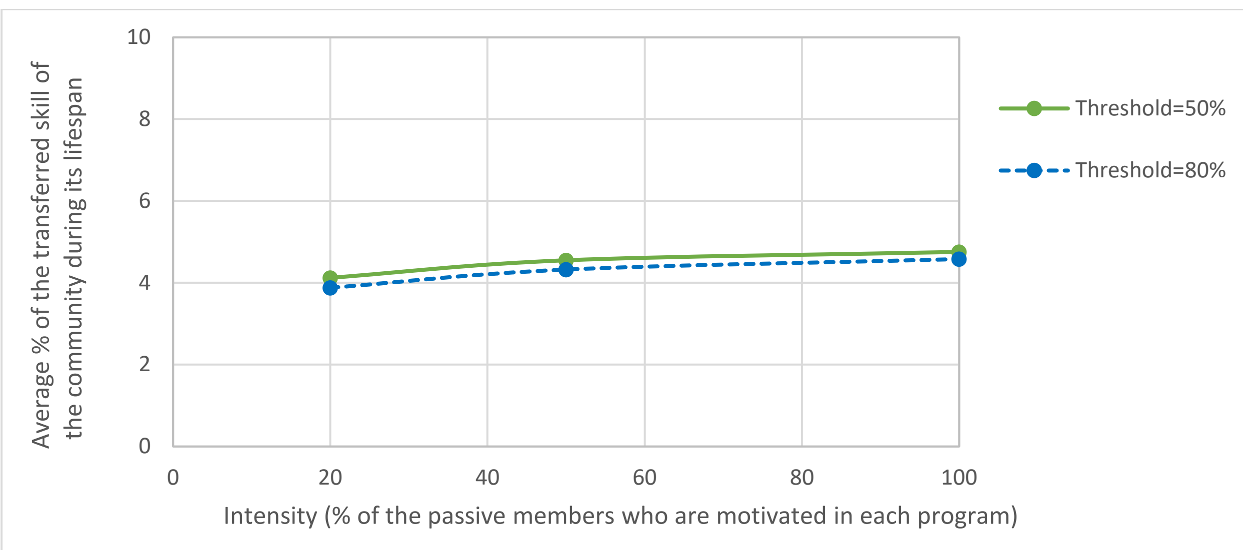


Figure 5-17: Comparison of average progression in skill levels (*Ats*) during the lifespan of a community, configured according to the 3rd series of experiments with various values of intensity and threshold of motivation programs.

The last performance indicator is the cost of motivation programs. The outcomes revealed that for programs with intensity value below 50%, there is a noticeable growth in motivation costs ($Mcost$), whereas the cost of these programs increased less sharply for intensity values above 50% (Figure 5-18).

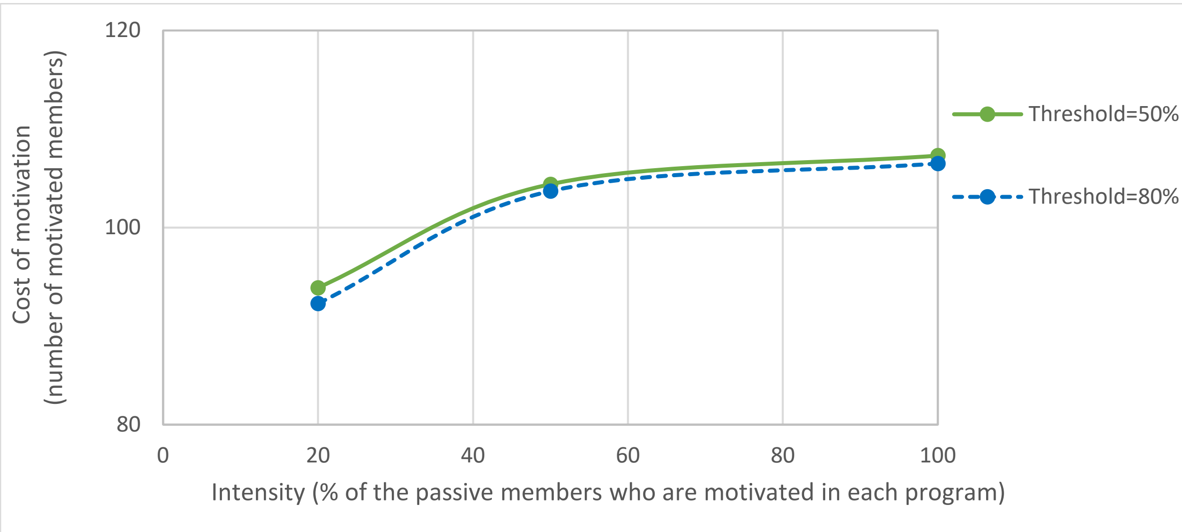
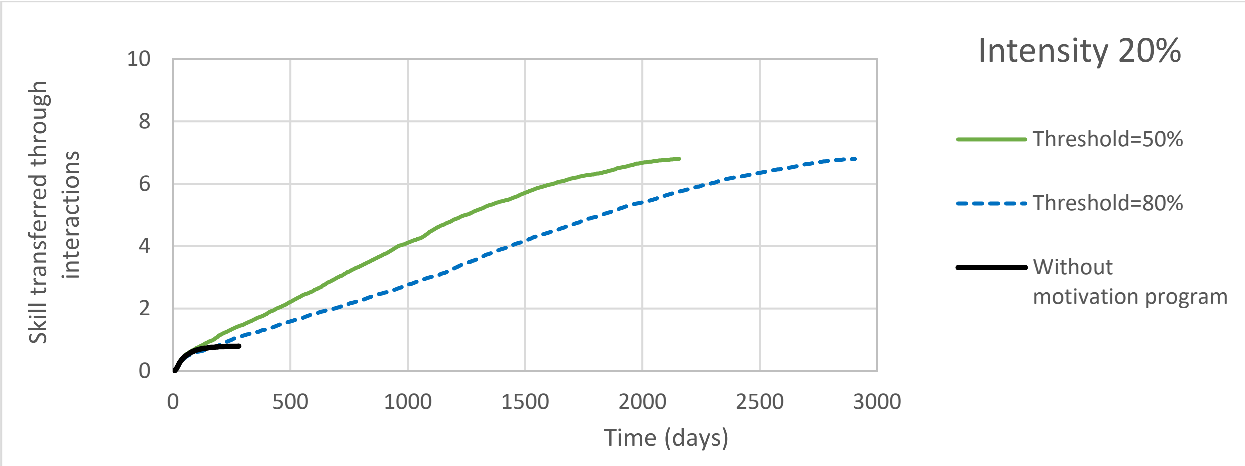


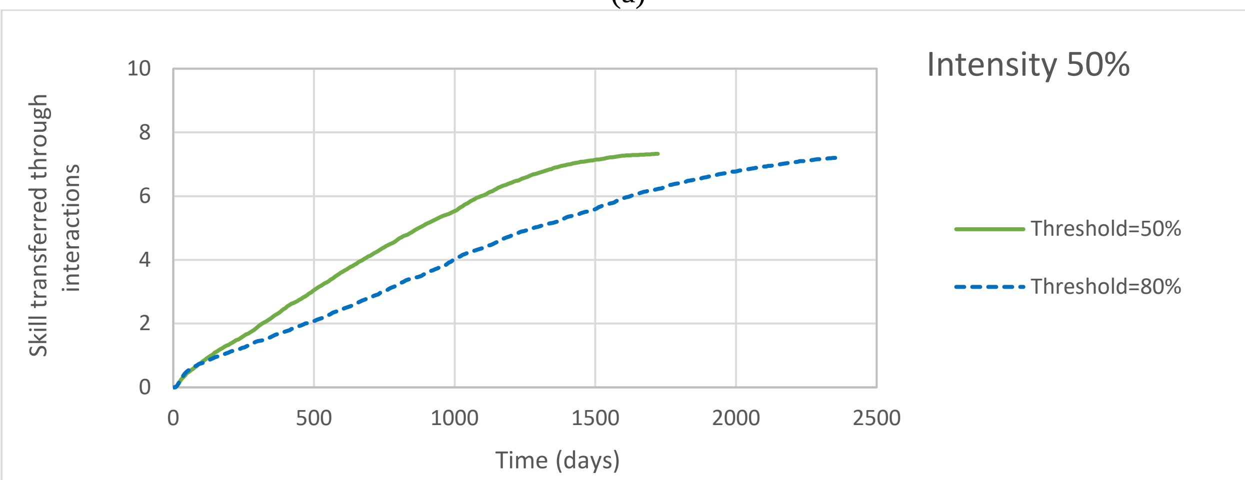
Figure 5-18: Cost of motivation programs ($Mcost$)

5.6 Discussion

In the last series of experiments, we studied the impact of motivation programs on community behaviors in terms of intensity and threshold. The results show that motivation programs can generally increase the lifespan, level of activeness, and transferred skill. However, more intense motivation programs may result in shorter lifespan but higher average of active members. It also reveals that the cost of motivation increases in more intense programs. Therefore, Fab Lab managers need to consider the costs and benefits of such programs based on their productivity.



(a)



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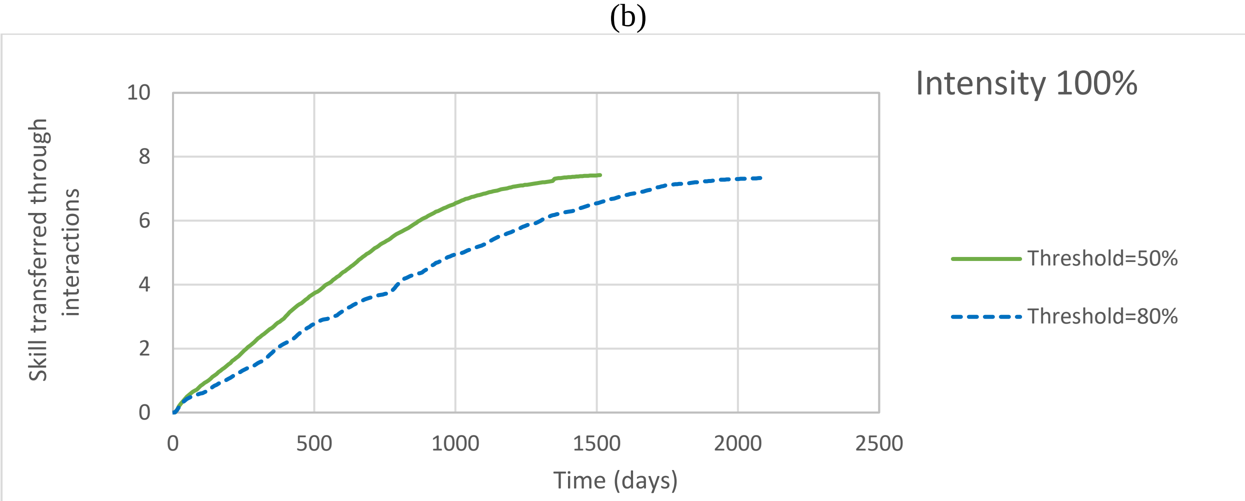

(c)

Figure 5-19: Skill level progression (Tts^t) of a community configured according to the 3rd series of experiments for different motivation programs in terms of intensity (*Imp*) and threshold (*Tmp*).

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

This final chapter focuses on the outcomes and the related conclusions of what has been studied through this research. From the discussions in previous chapters, results show that we achieved the main and all specific objective of the project.

We were able to develop a mathematical simulation model based on the theoretical analysis of Fab Lab communities. This model can properly address various configuration scenarios in order to study the interactions and collective behaviors of members. Then, we programmed a computer simulation using the AnyLogic platform, based on the proposed mathematical model. We also conducted several experiments. Since this study was not focused on any specific type of the Fab Lab community, we set the initial value of the communities parameters as generally as possible. Besides, we used normal distribution probabilities to set the initial values of all series of parameters and variables. For example, the levels of technology talent, exteroversion levels, and levels of interest to participate in the community for a set of members were initiated using normally distributed values. This simple configuration process let us to configure different communities easily. However, if necessary (for future studies), different types of distribution can be substituted instead of normal distribution to create specific type of Fab Lab community.

Moreover, we used evaluation techniques to validate the outcomes of the proposed model, besides two series of experiments for qualitative validation. Nevertheless, it is highly recommended for future studies to arrange empirical data gathering by simple questionnaires or using advanced sensors or magnetic cards, which can collect data whenever members use Fab Lab facilities. It is expected that comparing the current model outputs with real data may lead to assumptions that are more precise, which may improve the structure and concept of this model. Nonetheless, for particular conditions of experiments, we applied specific setups, which led us to explore different aspects of the Fab Lab communities.

The results of the first series of experiments shows the impact of initial skill levels of members on the community lifespan, as well as on the average percentage of the active members and the average skill transferred among members during the community lifespan. It shows that the lifespan of the community is longer for communities with lower levels of skills, provided that members have similar levels of interest to participate and levels of expectation to improve their skills.

These experiments show that one of the effective ways to increase the lifespan of the community and transferred skill is to have a community with diverse levels of skill, although it has a negative consequence on the average percentage of active members. Therefore, having members with diverse initial levels of skill is not recommended for Fab Labs that earn money from membership fees since it may cause less revenue. Likewise, this method cannot be helpful for institutional communities like labs in the universities or free associative communities where their priority is to involve more members. On the other hand, it can be useful by entrepreneurial Fab Labs for their crowdsourcing purposes because they are usually looking to increase interactions and skill or knowledge transfer. In this regard, the impact of the skills' number, which can represent the number of tools, equipment, or the technologies that a Fab Lab can offer to the members, seems to be next interesting criteria to be studied in future researches.

In the second step, we investigated the communication accessibility on members' interactions. The experiments revealed that the tendency of group working in communities with more available communication is higher. Differently, communities, which do not provide communication facilities, not only have more individual involvement than team working, but they also have more passive members who are interested in the Fab Lab; however, they cannot be involved due to their low skill levels or personal motivations. Accordingly, any media, which can facilitate the communication of the members in the Fab Lab communities such as newsletter, website, or social media pages, are highly recommended for all types of Fab Lab. For future studies, the size of the groups can be studied in details in order to discover in what conditions members can prefer to join together to work in big groups or interact only in small groups like groups with less than 5 members. This study would be very helpful for entrepreneurial Fab Labs, which are more willing to absorb members to participate collectively only in some limited number of big projects, or for institutional Fab Labs that expect numerous innovative ideas especially in the forms of university technology competitions.

Concerning the final series of experiments, we explored the impact of any motivation programs on several community behaviors. The study and comparative analysis of specific types of motivation programs was outside the scope of this research. Instead, motivation programs were investigated from two points of view including their threshold and intensity. The threshold is the limit of the percentage of passive members in the community that triggers the motivation program. On the other hand, the intensity concerns the percentage of the passive members who are motivated through the motivation programs. More intense programs can reactivate more percentage of the passive members and make them ready to participate in the community and interact again. The outcomes of the experiments confirm that regular motivation programs can significantly increase the productivity of the community in terms of lifespan, level of activeness, and transferred skill regardless of the intensity and threshold degrees of the programs.

Nonetheless, the results show that more intense motivation programs may result in shorter lifespan of the community but higher average of active members. Therefore, intense motivation programs seem more proper for Fab Labs that earn profit from their membership fees. Considering that the cost of motivation programs increases with higher intensity, Fab Lab managers are responsible to find the balance point between their costs and benefits depending on the productivity of their programs. Furthermore, the cost of motivation programs has a sharp increase for intensities up to 50%, but its cost does not increase much afterwards. That means that if any Fab Lab can afford the cost of motivation programs up to 50%, then a little increase in cost can lead to more intense programs too. In addition, programs with higher intensity or smaller threshold both can result in more average transferred skill. On the contrary, motivation programs for a community that has more passive members can increase its lifespan but decrease its level of activeness.

Finally, this research opens a new approach to model and simulate all kinds of skill-communities, such as Fab Labs. Beyond a master thesis, it can be considered as the beginning point for the similar studies and theoretical development.

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