When Human Service Meets Crowdsourcing: Emerging in Human Service Collaboration

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Abstract—With the sweeping progress of service computing technology and crowdsourcing, individuals are offering their capability as human services online. Companies are orchestrating human services for complex problem-solving, resulting in the rapid growth of human service ecosystems nowadays. Considering the unique characteristics of human services, like capability growth and human-involving collaboration, it is essential to understand the patterns of the development and collaboration among human services. Therefore, this paper proposes a three-layer time-aware heterogeneous network model to quantify the evolution in the human service ecosystem. Based on the model, an exploratory empirical study is presented to uncover how human service providers and consumers develop their capability in service provision and orchestration, as well as how human services collaborate with each other over time. Insights from the emerging patterns open a gateway for further research to facilitate human service adoption, including human service composition recommendation, human skill expansion suggestion, and systematic mechanism design.

Index Terms—Human as a service, heterogeneous network, human service provision and orchestration capability, emerging collaboration patterns, human service adoption

1 Introduction

With the rapid advancement of web technologies, the roles that individuals play over the Internet are changing, from passive browsers to active contributors who can proactively participate in different activities remotely to offer their expertise [1]. More and more individuals are now willing to offer their skills and capabilities as human services [2] through the web to solve complex problems for their clients, for example, *translating English to French or vice versa*, *proofreading 1,000 words in English within 24 hours*, *converting websites to iPhone and Android Apps* etc. As a consequence, several online human service platforms, such as Fiverr,[1] Upwork,[2] and Freelancers,[3] have emerged to provide markets for any individual or organization to offer *Human as a Service*. On the other hand, crowdsourcing has been considered as an effective model for many commercial companies as well as non-profit institutions to outsource tasks to external individuals or an extensive network of people for problem-solving [3], [4]. Amazon Mechanical Turk is the most famous crowdsourcing platform to leverage the wisdom of the crowd, not only for simple tasks like *hiring workers to extract purchased items from a shopping receipt*, but also for more complicated ones like *social science experiment* [5]. Hence, we are observing a rapid growth of human service ecosystems, driven by the development of human service markets and crowdsourcing technologies. Naturally, one straightforward but essential issue rises: *how to enable highly effective collaborations among these human services so as to solve complex tasks more efficiently?*

Recently, from the crowdsourcing perspective, many efforts have been conducted to extend the application of crowdsourcing beyond "micro-tasks" [3], [6], [7], to understand the motivation and behavior patterns of people when participating in crowdsourcing activities [8], and to design strategies for reputation evaluation [9] and optimization [10], or skill utility evaluation [11], [12]. From service computing perspective, many approaches have been proposed to support the web service composition [13], [14], [15], [16], [17], service recommendation [18], [19], [20], [21], [22], as well as dynamic business process [23]. Furthermore, some researchers turn to study the collaborations in the online web service ecosystem such as mashup-service ecosystem [24], [25] and scientific workflow-service ecosystem [26] to optimize the web services applications. If human services are provided and consumed in the same way as web services, then these approaches can be directly applied to compose human services for complex task solving. However, the following two unique characteristics make human services significantly different from web services:

1. www.fiverr.com
2. www.upwork.com
3. www.freelancers.com

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- *Development of Human Capability*.

Human factors play the core role in a human service ecosystem. On one hand, the capabilities of providers who offer services are growing over time so that they may offer more and more services as time goes by. On the other hand, the consumers who use human services can learn from their past experiences and improve their abilities for service orchestration, so that they can manage those human services more effectively and efficiently. It is therefore challenging to study and understand the interactive patterns in such an ecosystem that is constantly self-growing.

- *Different Collaboration Mechanism*.

Web services collaborate with each other through their inter-operational APIs. On the contrary, for human services, their collaborations are based on the interpersonal communications between consumers and providers. Such a collaboration requires the managerial skills of the consumers to distribute a complex project to a group of human service providers. Hence the web service orchestration approach based on service's interface cannot be applied to human service orchestrations, as the human services do not have the notion of definable interfaces. Moreover, in the practise, collaborations among human services will change over time.

The goal of this project is to *extend the research from services themselves to the providers and consumers, with a focus on the collaboration among human services in the contemporary human service ecosystem. This project attempts to open a gateway for further research on leveraging human service compositions to solve complex tasks*. As an extension from the earlier study [27], in this paper, a comprehensive quantitative model is developed to evaluate the growth and identify the emerging patterns for human service collaboration, including the growth of human service provision capability, evolution of human service orchestration capability, as well as the emerging collaboration patterns among services. Based on the data collected from Fiverr.com, which is a popular human service platform with rich publicly available data and simple extensible operation model, we have conducted a collection of empirical studies. Our substantial findings have demonstrated that, clear patterns exist in the self-development of human service provision and orchestration, which potentially can be exploited to effectively improve human service adoptions. In particular, those patterns can help us to develop effective human service recommendation models, personal skill expansion strategy and systematic support for human service platform. The main contributions of this paper are two-fold:

- A comprehensive exploratory empirical study on a real human service platform is conducted and reported, which uncovers the emerging patterns in a human service ecosystem.
- A network-based quantitative model to understand the growth patterns in human service ecosystem is developed, to study the evolution of human service provision, consumption and collaboration.

The rest of this paper is organized as follows. Section 2 summarizes the related work in web service and crowdsourcing perspectives. Section 3 presents the network-based quantitative model. Section 4 shows the data collection and cleaning methodology. Section 5 develops the analysis methodology to uncover the empirical patterns. Section 6 discusses the adoption based on the discovered insights. Section 7 draws conclusions.

2 Related Work

2.1 Web Service Collaboration

With the rapid development of web services in the past years, many researchers have studied the evolution of the web service ecosystem. The network analysis methodology is introduced into the scientific service-workflow ecosystem, to understand the collaboration patterns among scientific services [28]. The dynamic patterns in the mashup-service ecosystem are studied [29] and then the link prediction-based methodology is developed to predict the evolution of service composition [18]. Some services may become unavailable and have to be replaced by alternative ones to guarantee the compositions' reliability [30]. Therefore, some researchers leverage the service evolution patterns to develop applications such as service recommendation [20]. To illuminate the applications of the newly emerged services [31], a Divide-and-Conquer approach is developed to facilitate the newborn services recommendation [32]. The dynamic of the service's functionality is considered to further improve the performance [21], [33]. Reputation network [25], [26], for example, is an approach to develop a trust network in order to recommend trustworthy services and workflows.

In the same vein, automatic service composition is another intensively investigated topic in service computing. Various techniques have been developed to discover and compose relevant services as a composition for complex tasks [13], [14], [17]. For example, Aalst [34] proposes a framework named "TomTom4BPM" that adopts process mining technique for various purposes, such as comparing the actual process execution with pre-modeled ones and dynamically navigating during process exceptions. A time-aware service recommendation approach is presented for mashup creation, integrating topology, content and temporal information [20].

Hence, we can see that a number of approaches have been developed to improve the performance of the web service recommendation and composition. However, the publicly available web services nowadays are still scant which limit the application of these approaches. On the other hand, recently, with the wide adoption of servitization, human service ecosystem emerges as an booming marketplace to connect human service providers and consumers to solve complex tasks, predicted to create substantial economic impact on the entire society [35]. As discussed before, the unique characteristics such as the human factors and the change of collaboration mechanism make the human services different from web services. It is necessary to obtain an in-depth understanding of the service provision, consumption and collaboration in the human service ecosystem.

2.2 Crowd Sourcing Platform

Recent years have witnessed the rapid growth of crowdsourcing platforms where businesses/consumers and service providers make exchanges on human labour in an on-demand manner [36]. More importantly, the outsourcing tasks are not only just simple, small pieces of "microtasks."

Instead, individuals, even some small organizations, are willing and able to share their capabilities through these platforms to solve some highly-skilled tasks like website development, graphics design, personalized route guidance [6] and fine-grained recognition [3].

Given the huge number of tasks posted in the crowdsourcing platforms, it is important to match the requests to service providers in an appropriate way to reduce the search cost and increase the service quality [37], [38]. To fulfill this goal, many studies yield the worker-skill model to organize the human services, with consideration of skills in a single domain [39], [40] and multiple-domain perspectives [11], [37], [41], [42], [43], [44]. In the recent literature, the hierarchy of skills is introduced to improve the task assignment accuracy [38]. A Hidden Markov Model (HHM) is developed based on observed characteristics (such as certification, feedback score, hiring rate, rehire rate, compensation wage from previous tasks etc.) to evaluate the expertise level a service provider has for a given skill, in order to facilitate the expert searching [12]. Works like [9], [45] attempt to model the trust and reputation aspect of the crowd and use the model to recommend service providers. From the other prespectice, some researchers [47] further develop systems to recommend suitable tasks for the service providers in order to improve the overall performance.

Human characteristics play a critical role in the crowdsourcing platform. Some researchers study the motivation of a provider undertaking crowd sourcing jobs and how they participate in different tasks [8]. Law and Yin etc. [48] study the communications among the crowd and investigate how such communication can affect the outcome of tasks. As the crowdsourcing tasks will cost the consumers money for the hiring, some strategies are presented to optimize the task decomposition and reduce the total cost [49]. Considering the fact that service providers may have diverse qualities, some studies have attempted to infer the high quality service providers and predict the true answer through aggregating all providers' answers [7], [42].

One important obstacle for the further booming of the crowdsourcing platform is that human service providers are disincentivized from learning new skills [45], and they consider the crowdsourcing platforms as places to seek temporary jobs for their existing skills [50]. To mitigate such a challenge, Atelier is developed to introduce the micro-internship to connect the service providers with mentors who have experience in a given skill [51]. Kokkodis and Ipeirotis try to predict the performance of a provider in new skills based on the prior, category-specific feedback [45]. However, our knowledge about the evolution of these crowdsourcing platform is still very limited.

2.3 Human Service: Web Service with Crowdsourcing

In contrast to these related works, this paper combines service computing perspective and the crowd sourcing research to study the emerging human service ecosystem. Unlike the traditional web services, in the case of human services, intuitive enough, the human factor plays a critical role for service recommendation and composition. Compared with the typical crowdsourcing tasks, human services usually exhibit a much higher level of complexity and interactions that the insights from the dynamic patterns will have profound implications. Therefore, as an extension to our previous work [27], in this paper, we focus on the evolution of the human service ecosystem. In particular, we are interested to explore questions like how providers grow their provision capability to offer more services, how consumers grow their capabilities to orchestrate services for complex task, and what are the emerging patterns among the human services' collaboration.

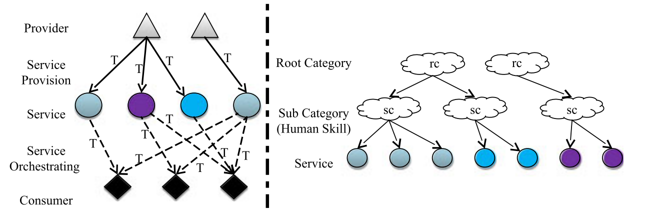

Fig. 1. Operation model and functionality instrument for human service ecosystem. (a) Three-layer time-aware heterogeneous network model. Specially, each link is allocated with the time when such relation occurs in the ecosystem. (b) Tree-structure hierarchy for human services. sc refers to the sub category, rc refers to the root category.

3 Network Model and Research Questions

3.1 Network Model for Human Service Ecosystem

3.1.1 Operation Model

Human service ecosystems are typically two-sided markets [52], organized around human service platforms. Operating under a similar fashion, these platforms serve as service marketplaces to connect service providers and consumers. Consider the *Freelancers.com* as an example. The *Freelancers* are service providers with specific sub category (skill) set(s). They can create their accounts in the platform with profiles to describe the services they can provide, and their respective prices. Consumers define the content of their projects, the expected due date and the budget, then post the tasks on the platform, or send the projects to some potential relevant providers who can contribute to the projects. After communications between the service consumers and the providers, a provider can be hired and then begins to work on the project. Upon completion, the service provider will deliver the outcome via the platform. The consumer will make the payment if the requirements are adequately satisfied, and then rate the quality of the service. Therefore, the operation model in these market places is intuitive: *human service providers offer their skills while consumers hire these services to solve complex problems*, which can be formally defined as a three-layer nnetwork, as shown in Fig. 1a.

Definition 1 (Heterogeneous Network Model for Human Service Ecosystem, G). *A human service platform can be formally defined as a three-layer time-aware heterogeneous network* $G = \{P, S, C, R_{ps}, R_{cs}\}$ *where* S, P, C *refer to the human services, services providers and consumers respectively.* $R_{ps} = \{r_{ps} = <p_i, s_j, t>\}$ *refer to the provision relations where each triple represents that provider* p_i *registered service* s_j *on the platform at* t. $R_{cs} = \{r_{cs} = <c_k, s_j, t>\}$ *refer to the orchestrating relations where each triple represents that consumer* c_k *used service* s_j *at* t.

3.1.2 Functionality Hierarchy

To facilitate the organization of the massively available human services in the ecosystem and reduce the search cost, the hierarchical taxonomy [38], [53] based on service functionality are used to organize human services into a multi-layer instrument. In this paper, we will use a three-layer framework as shown in Fig. 1b.[4] Specially, we can define a human service as follows:

$$s_j = <p, fs, sc, rc>, \tag{1}$$

where p refers to the service provider, fs refers to the service's functionality. sc refers to the specific category it belongs to. In this paper, we name it as *sub category*, or *"skill"*. rc refers to the more general category to which sc belongs, in other word, its parent node in the tree-structure hierarchy. As we use the three-layer hierarchy in this paper, rc will be the root node so that we name it as *"root category"*, or *"domain"*. In this paper, we will only use *"root category"* for consistency.

3.1.3 Lifespan Timeline

In the human service ecosystem, continuously, new service providers will join the platform and offer their capabilities as new human services; in the meantime, new consumers will join the platform to hire service providers for their projects. To evaluate the growth of provision and orchestration capability of the providers and consumers since they join the ecosystem, we need to calculate the timeline for each provider and consumer as they joined the platform at different times. Therefore, given the network G for a human service ecosystem, we can formally define the join time for each provider and consumer as follows:

Definition 2 (Join time for Provider). *Given a provider p_i, the join time $ft(p_i)$ represents the time he/she published the first service in the platform:*

$$ft(p_i) = min\{r_{ps} \to t | r_{ps} \in R_{ps}, r_{ps} \to p = p_i\}. \tag{2}$$

Definition 3 (Join Time for Consumer). *Given a consumer c_k, the join time $ft(c_k)$ represents the time interval that he/she purchased the first service in the platform:*

$$ft(c_k) = min\{r_{cs} \to t | r_{cs} \in R_{cs}, r_{cs} \to c = c_k\}. \tag{3}$$

Based on these definitions,[5] we can get the lifespan time line for each provider and consumer as:

Definition 4 (Lifespan Timeline for Provider/Consumer). *Given a time interval t, for the provider p_i with join time $ft(p_i)$, the lifespan timeline is $lt(t, p_i) = t - ft(p_i)$; for the consumer c_k with join time ft_{c_k}, the lifespan timeline is $lt(t, c_k) = t - ft(c_k)$.*

3.2 Research Questions

As discussed above, one of the unique characteristics for human services is that the capability of service provision and service orchestration can grow as providers and consumers become mature in the platform. Naturally, we are interested in such capability growth for both providers and consumers:

- *Q1: Provision Capability Growth*: how do the providers grow their provision capability over time? Specially, how fast and in what pattern does a provider develop a new human service?
- *Q2: Orchestration Capability Growth*: how do the consumers grow their orchestration capability? Specially, how and in what pattern does a consumer purchase services?

Furthermore, the collaborations among human services are based on the orchestration of the consumers, the communication between the providers and consumers, instead of the predefined inter-operational APIs. Naturally, it is important to understand the collaboration patterns which reveal how different human services are used together to solve complex tasks requested by consumers.

- *Q3: Service Collaboration Pattern*: what are the emerging patterns among human services as time goes by? Specially, whether the human services collaborate randomly?

To answer these questions, in the following section, we collect related data from Fiverr.com platform. For each question, we develop quantitative methodology and then report the observations from the empirical study. Though we only use the data from Fiverr.com as the example, our model and methodology can be applied to study other similar platforms like Upwork and Freelancers.

4. We use the three-layer hierarchy here as it was used in the Fiverr.com platform when we collected the data for the empirical study. Naturally, it is very easy to extend to more complex tree-structure hierarchy. Additionally, how to optimize the hierarchy is out of scope in this paper and some related approaches can be found in the previous work [20], [25], [54].

5. Note that these definitions also reveal the methodology to calculate the metrics. Due to the space limitation, in this paper, instead of presenting the detail algorithm, we will just use the definitions to show how we calculate each quantitative metric.

Fig. 2. Example of information about human service on Fiverr.com

4 Data Collection and Overview

4.1 Data Collection

In this study, we chose Fiverr.com as our subject platform for several reasons. First, it is one of the most popular human service platforms. Second, its publicly available data is rich, including service provider, sub category (skill), root category, historical purchases and time-stamps. Third and more importantly, it allows a user to rate and comment a service after a purchase is finished. Fig. 2 shows a screen shot over a translation service on Fiverr.com. We can see that the service provider offers the service for \$5, which is in the sub category *"Translation"* within root category *"Writing & Translation"*. Consumer can rate with stars and provide comments. Using the time-stamps of the comments and ratings, we are able to group the purchases made by the same consumer within a small observation window.[6]

To avoid extreme sparseness in the dataset, we fetched the information about the top rated services on Fiverr.com. For these service providers, we further obtained all their

6. It is assumed in this study that those purchases made by one consumer in the same observation window (30 days) are for the same or closely related project(s). While this assumption is certainly not perfect, it is reasonable to assume the different efforts made by the same individual in the small observation window, are correlated in some way.

TABLE 1
Data Statistics between Jan. 2015 and Jan. 2016

	Before Abnormal purchase clean	After Abnormal purchase clean
Purchase Number	2,385,552	2,288,255
Consumer Number	772,722	726,926
Service Number	101,010	95,835
Provider Number	41,771	40,049
Transaction Number	1,095,444	1,093,742
Root Category Number	11	11
Sub Category Number	117	117

registered services. Note that in Fiverr.com, if a service is purchased in the past 30 days, in its transaction history this purchase will appear as "* days ago"; if it is purchased within one year but more than 30 days, it will appear as "* months ago"; otherwise, it will appear as "* years ago." For each service, we only got the most recent 5,000 purchased records even if it is consumed more than 5,000 times. Using this strategy, we successfully retrieved a dataset consisting of 101,010 services, 41,771 providers, 772,722 consumers, and 2,385,552 purchase records between January, 2015 and January, 2016.

4.2 Abnormal-Purchase Cleaning

Like many other social platforms, Fiverr provides a user rating system so that consumers can choose the purchased services based on the feedbacks from other customers. Therefore, there is a strong connection between the rating and the financial gains for the service providers and it is desirable for one to have many good reviews as well as good comments. Such a rating system is subject to many types of attacks [55], [56]. One example of attack is called "self-promoting" [9], which refers to the case where a provider herself hires another person to make fake transactions and leave good ratings and comments.

In practice, it is extremely unlikely for one to hire more than 30 service providers in a month, given the average job delivery time frame is two to three days. Therefore, it is reasonable for us to filter out all the transactions[7] made by the customers who have used more than 30 services monthly, to reduce the potential impact from these abnormal purchases. For example, the consumer *"/piercelilholt"* purchases 96 services in a month while his description is wrote as *"This is where you make your pitch to potential buyers. Describe your background, your passion and your personality."* Obviously, these purchases are abnormal-purchases which should be filtered for further analysis.[8] As shown in Table 1, removing these abnormal-purchase records can guarantee the significance of the empirical study, while still keep the integrity of the data: we remain more than 95.73 percent of purchase records and 99.84 percent transactions.

4.3 Overview

After removing the potentially abnormal purchase transactions, based on the heterogeneous network proposed in Section 3.1, we can calculate the *distribution of service popularity*, defined as the distribution of output degree for services; the *distribution of providers' services number*, defined as the distribution of output degree of provider nodes; the *distribution of purchase number*, defined as the input degree of consumer nodes. Additionally, we calculate the *distribution of transaction length* which refers to the number of transactions with a given number of services. As reported in Fig. 3, it can be seen that:

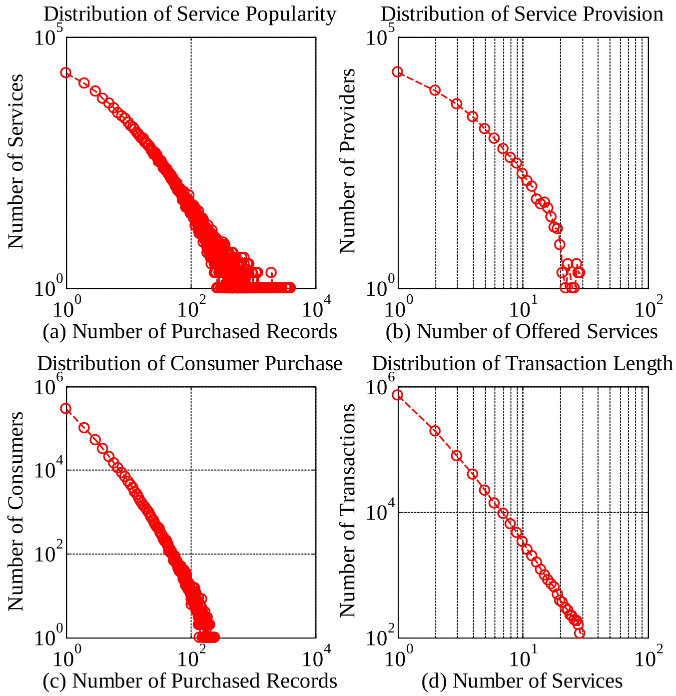

Fig. 3. Distributions. (a) Distribution of service popularity refers to the number of services used in a given number of purchases; (b) Distribution of service provision refers to the number of providers with a given number of registered services; (c) Distribution of consumer purchase refers to the number of consumers who purchase a given number of records; (d) Distribution of transaction length refers to the number of transactions with a given number of services in it.

The distribution of service popularity meets the long-tail power law distribution. This means that a few services are much more popular than the rest. The most popular service is *"do-a-book-cover-or-a-movie-poster-for-you"* offered by provider *"/janielescueta"* with 4,013 purchase records.

From the distribution of service provision, most providers only offer one service while a few providers will even offer more than 20 services. For example, *"/psychicsunshine"* offers 29 different services, most belonging to the root category *"Lifestyle"*.

Most consumers only buy a few services while some experienced consumers purchase many services to solve their problems. For example, *"/gninja21"* consumes 246 services in one year. Our data also shows that 13,192 consumers are not only just using the services in the platform, instead, they become a provider to offer their capabilities. For example, *"/mayasayvanova"* offers services such as *"I will write an AWESOME About page"* in *"Writing & Translation/Business Copywriting"* while she also purchases the service *"I will be Your Book Editor And Proofreader"* to guarantee the quality.

Most transactions only require one service while only a few use more than ten services. Apparently those transactions

7. We define the purchases from the same consumer in one month as a transaction.

8. Note that in this paper, we will leave the study about how to improve the abnormal-purchase detection as the future work and just remove these apparent abnormal-purchases to minimize the impact of such attacks.

with more than one services can help us understand how the human services collaborate with each other.

5 Empirical Result

5.1 Provision Capability Growth

Q1.1: How fast do providers develop a new service?

In a live service network, the registered services can be considered as the collection of the provision capability for the given provider. A provider will over time, expand her skills to offer new services to effectively grow the potential customers and in turn, increase the revenue. Hence, to study the growth of the provision capability, we remove all the services purchased before January 2015 and get 32,468 providers who join the platform during our study period. For each provider p_i and a given time t_j, we define the following metrics to quantify her provision capability:

- *Ever Provided Services (EPS)*: all the services provided by p_i until t_j.

$$EPS(p_i, t_j) = \{r_{ps} \rightarrow s | r_{ps} \rightarrow p = p_i, r_{ps} \rightarrow t \leq t_j\}. \quad (4)$$

- *Ever Provided Sub Categories (EPC)*: all the related sub categories (skills) provided by p_i until t_j.

$$EPC(p_i, t_j) = \{s \rightarrow sc | s \in EPS(p_i, t_j)\}. \quad (5)$$

- *Ever Provided Root Categories (EPRC)*: all the related root categories provided by p_i until t_j.

$$EPRC(p_i, t_j) = \{s \rightarrow rc | s \in EPS(p_i, t_j)\}. \quad (6)$$

Naturally, we can calculate the incremental for these three metrics as:

- *Newly Provided Services (NPS)*: the services provided by p_i at t_j.

$$NPS(p_i, t_j) = EPS(p_i, t_j) - EPS(p_i, t_j - 1). \quad (7)$$

- *Newly Provided Sub Categories (NPC)*: the sub categories (skills) first provided by p_i at t_j.

$$NPC(p_i, t_j) = EPC(p_i, t_j) - EPC(p_i, t_j - 1). \quad (8)$$

- *Newly Provided Root Categories (NPRC)*: the root categories first provided by p_i at t_j.

$$NPRC(p_i, t_j) = EPRC(p_i, t_j) - EPRC(p_i, t_j - 1). \quad (9)$$

Furthermore, for each provider p_i and a given metric $PC \in \{EPS, EPC, EPRC, NPS, NPC, NPRC\}$, we sort the provision capability by the time interval as $\{PC(p_i, t_{i,1}) ... PC(p_i, t_{i,n_i})\}, t_{i,1} < ... < t_{i,n_i}$ and then evaluate her capability over her lifespan as $\{PC(p_i, lt_{i,1}), PC(p_i, lt_{i,2}) ... PC(p_i, lt_{i,n_i})\}$ where $lt_{i,j} = lt(t_{i,j}, p_i)$.

Finally, for the human service ecosystem G, we can calculate the service provision capability for each provider and then use their average to reveal the ecosystem's service provision capability:

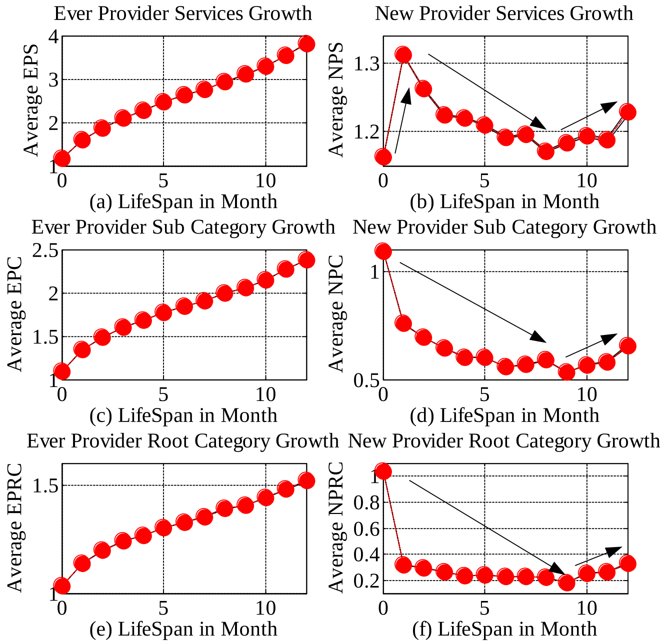

Fig. 4. Growth of service provision capability in the human service ecosystem, Fiverr.com.

$$APC(lt_j) = \frac{\sum_{p_j \in P} |PC(p_i, lt_j)|}{|\{p_i | p_i \in P, PC(p_i, lt_j) > 0\}|}, \quad (10)$$

where $PC \in \{EPS, EPC, EPRC, NPS, NPC, NPRC\}$.

As shown in Fig. 4, the number of the ever provided services, ever provided sub categories and ever provider root categories are all increasing as time goes by, indicating the fact that *providers are developing their capability to provide more services and become more competitive in the ecosystem*.

Additionally, it can be seen that after a rapid increase at the very beginning, the growth of the services slows down for a certain period and then increases again. This is because when a provider joins the platform, she would register all the services she is capable to provide and then it becomes more and more difficult to expand, resulting into a *diminishing marginal utility* at the beginning of her lifespan. As time goes by, she eventually is able to acquire some new marketable skills that can be developed into new services for the platform. However, our result shows that this first stage costs the providers about eight months in average, which is a long period for developing new services.

Furthermore, from Figs. 4d and 4f, we can see that comparing to developing a new service in the same sub category (skill), developing a new service in a different sub category (skill), or even in a different root category is much more difficult as the average NPC and NPRC is much lower than the average NPS.

Observation 1. The providers' provision capability in the ecosystem, including services, sub category (skill), new root category, is increasing with a "diminishing marginal and then increase" pattern, as they grow mature in the platform. However, the current learning curve is quite long, which is about eight months. This slow learning process hints some opportunities for improvement.

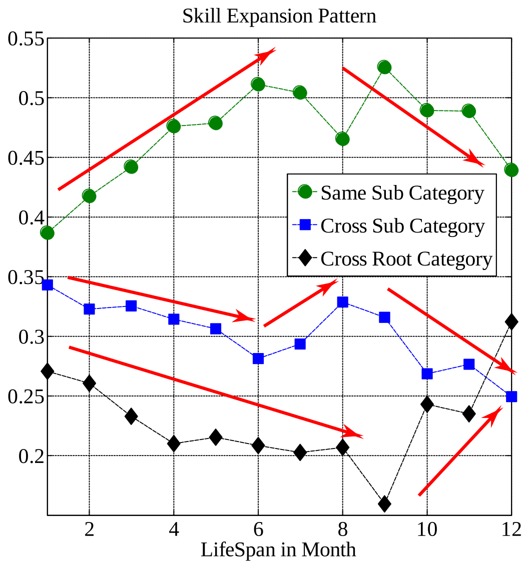

Fig. 5. Expansion pattern for new provided services.

Q1.2: In what pattern do providers develop a new service?

To evaluate how providers develop a new service, for each new service $s_k \in NPS(p_i, lt_j)$ we can identify three expansion patterns based on the functionality hierarchy:

- *Same Sub Category*: refers to the case where provider develops new service in a ever registered sub category (skill).

$$s_k \rightarrow sc \in EPC(p_i, lt_j - 1). \tag{11}$$

- *Cross Sub Category*: refers to the case where provider develop new service in a new sub category (skill) but still belongs to a ever registered root category.

$$s_k \rightarrow sc \notin EPC(p_i, lt_j - 1), s_k \rightarrow rc \in ERPC(p_i, lt_j - 1). \tag{12}$$

- *Cross Root Category*: refers that one develops a new service in a new root category.

$$s_k \rightarrow rc \notin ERPC(p_i, lt_j - 1). \tag{13}$$

Expanding one's capability over a new sub category (skill) or root category is difficult, which is clearly presented in Fig 5. It can be seen that the percentage of the *"same sub category"* is much higher than the other two during our study period. In particular, we can separate the sub category (skill) expansion into three phases:

- *At the beginning (1-6 months)*, the percentage of "same sub category" is increasing, indicating that providers intend to develop new services in the sub category that they are familiar with.
- *After that, during 6-8 months*, we can observe an increase for the "cross sub category", which means that the service provider is turning to develop new services in the neighbouring fields.
- *Finally (9-12 months)*, the providers are able to publish new services in new root category that the percent of the "cross root category" is increasing.

This is consistent with our observations of the capability growth because they both show how the provider goes through the "learning curve" for the human service provision, growing from novice to mature enough to provide diverse human services in the ecosystem.

Observation 2. The providers tend to offer services with similar functionality and then diversify to the other sub categories (skills) or root categories in the functionality hierarchy, indicating the latent relations between different skills.

5.2 Service Orchestration Capability Growth

Q2.1: How do consumers purchase services for problem solving?

Service orchestration refers to the case where the customer uses more than one service for his project. Such a customer will need to exercise his managerial skills in order to coordinate the efforts of multiple service providers to serve for some complex task. The data collected from Fiverr.com cannot tell which project the transactions were made for, therefore, we need to make an assumption. In this study, we would like to assume that *the transactions made by one customer in a one-month time frame are serving the same or related projects*. Note that this assumption here is not perfect because it is arguable that one may hire different services at the same time for different projects. However, it is reasonable for us to assume that even when these services are hired for different projects, these projects are somehow related. In addition, it is possible that there are some agencies hiring services for different end consumers. However, there is no information available to distinguish such agencies from others while normally the fraction would be related small.

Therefore, in this paper, we consider the complexity of the services purchased in the same one-month time frame as the consumer's orchestration capability. To quantify this orchestration capability, given a consumer c_k and the time t_j, we can define the following metrics to represent the orchestrating capability:

- *Orchestrating Services (OS)*: the services purchased by c_k during t_j.

$$OS(c_k, t_j) = \{r_{cs} \rightarrow s | r_{cs} \rightarrow c = c_k, r_{cs} \rightarrow t = t_j\}. \tag{14}$$

- *Ever Orchestrating Services (EOS)*: all the unique services purchased by c_k until t_j.

$$EOS(c_k, t_j) = \{r_{cs} \rightarrow s | r_{cs} \rightarrow c = c_k, r_{cs} \rightarrow t \leq t_j\}. \tag{15}$$

- *New Orchestrating Services (NOS)*: the new unique services purchased by c_k during t_j.

$$NOS(c_k, t_j) = EOS(c_k, t_j) - EOS(c_k, t_j - 1). \tag{16}$$

Similarly, we can define the *Orchestrating Root Categories/Sub Categories/Provider*, *Ever Orchestrating Root Categories/Sub Categories/Provider* and *New Orchestrating Root Categories/Sub Categories/Provider* for each consumer. Hence we can get 12 metrics to evaluate each consumer's orchestration capability over time. Similar to the provision capability measurement, for each metric OCM in these 12 indicators,

TABLE 2
Quantitative Metrics for Service Orchestration Capability

Service Orchestration Capability	Description
Orchestrating Services (OS)	Services purchased during the given time interval by consumer
Ever Orchestrating Services (EOS)	Services purchased by consumer
New Orchestrating Services (NOS)	New services purchased during the given time interval
Orchestrating Root Category (ORC)	Root categories purchased during the given time interval by consumer
Ever Orchestrating Root Category ($EORC$)	Root categories purchased by consumer
New Orchestrating Root Category ($NORC$)	New root categories purchased during the given time interval
Orchestrating Sub Category (OC)	Sub categories purchased during the given time interval by consumer
Ever Orchestrating Sub Category (EOC)	Sub categories purchased by consumer
New Orchestrating Sub Category (NOC)	New sub categories purchased during the given time interval
Orchestrating Provider (OP)	Providers the consumer interact with during the given time interval
Ever Orchestrating Provider (EOP)	Providers the consumer ever interact with
New Orchestrating Provider (NOP)	New providers the consumer interact with during the given time interval

we sort the values based on time interval as $\{OCM(c_k, t_{k,1}) \dots OCM(c_k, t_{k,n_k})\}, t_{k,1} < \cdots < t_{k,n_k}$ and then map to the lifespan as $\{OCM(c_k, lt_{k,1}), OCM(c_k, lt_{k,2}) \dots OCM(c_k, lt_{k,n_k})\}$ where $lt_{k,j} = lt(t_{k,j}, c_k)$. Finally, given the human service ecosystem G, we can define the service Orchestration capability as the the average of all the consumers' Orchestration capability:

$$AOC(lt_i) = \frac{\sum_{c_k \in C} |OCM(c_k, lt_i)|}{|\{c_k | c_k \in C, OCM(c_k, lt_i) > 0\}|}, \tag{17}$$

where OCM refers to the 12 different measurements summarized in Table 2. Using the dataset after cleaning the suspicious purchases, we can quantify the service orchestration capability as reported in Fig. 6. It can be seen that:

After a slight decrease, the average number of services (OS), sub categories (OC), root categories (ORC) and providers (OP) used in each transaction is increasing more and more rapidly. This means that consumers are able to orchestrate more services and providers to deal with their complex requirements.

Similar to the provision capability, the number of new service orchestration and provider orchestration decrease first and then increase. However, it can be seen that the length of the "diminishing marginal utility" effect is much shorter than the service provision capability, which means that *comparing with the provider, it is much easier for the consumers to grow their capability to use the human services in their business.*

However, the number of orchestration over services in different sub categories and root categories is constantly decreasing, indicating that the consumers are not good at developing more and more new complex requirements. One reason for this is that the consumers' requirement is associated with their business while the business scope is limited. This is consistent with the fact that currently

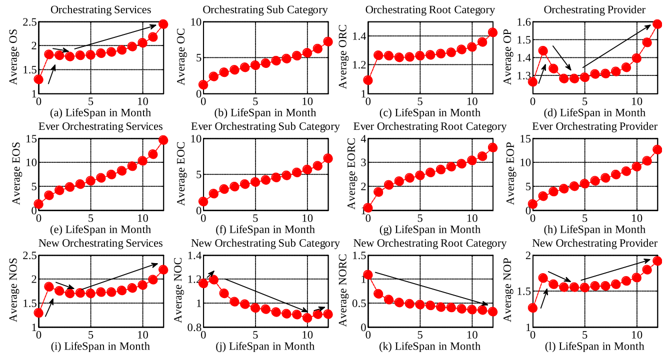

Fig. 6. The growth of service orchestration capability overtime in Fiverr.com during Jan. 2015 and Jan. 2016.

consumers consider the platform like Fiverr as a marketplace to seek temporary capability complement rather than long-term perspective [45].

Observation 3. Consumers are capable of orchestrating multiple services, including services in different sub categories and root categories. This capability grows as they become more familiar with the orchestration process and the learning curve is much shorter than the case where providers attempt to provision new services. However, consumers fail to continuously develop more complex requirements in the platform.

Q2.2: How do consumers purchase a new service?

As we have observed that the consumers grow their service orchestration capability over time, naturally, we are interested in knowing how consumers purchase a new service in the platform. Given a consumer c_k, for each new service $s_j \in NOS(c_k, lt_i)$, we can identify the following four extension patterns:

- *Same Sub Category*: refers to the case where one purchases new service in the same sub category.

$$s_j \rightarrow sc \in EOC(c_k, t_j - 1). \tag{18}$$

- *Cross Sub Category*: refers to the case where one purchases the new service in the sub categories never used before but still belongs to the ever used root categories.

$$s_j \rightarrow sc \notin EOC(c_k, t_j - 1), s_j \rightarrow rc \in EORC(c_k, t_j - 1). \tag{19}$$

- *Cross Root Category*: refers to the case where one purchases the new services in the root categories never used before.

$$s_j \rightarrow rc \notin EORC(c_k, t_j - 1). \tag{20}$$

- *New Provider*: refers to the case where one purchases the new services offered by the providers never collaborated with before.

$$s_j \rightarrow p \notin EOP(c_k, t_j - 1). \tag{21}$$

Fig. 7 shows how the consumers purchase new services over time. It can be seen that, different from the expansion

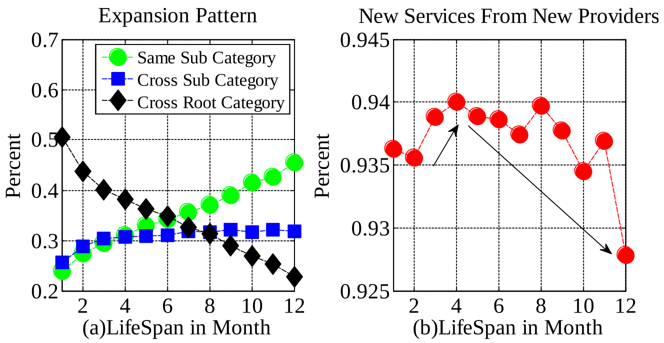

Fig. 7. Service orchestration expansion patterns for consumers.

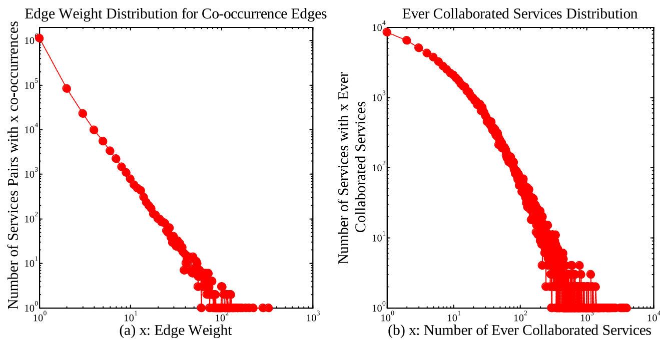

Fig. 8. Distributions for service co-occurrence network.

of the sub category (skill) provisioning, the percentage of the "same sub category" is increasing while the "cross root category" is decreasing.

This means that as time goes by, the consumers are more likely to orchestrate services in the same sub category. Two possible scenarios for this type of orchestration are 1) split a complex job into a number of smaller tasks of same (or similar) type(s) which are completed by a group of service providers in parallel; and 2) apply a redundancy strategy by hiring more than one provider to work on the same job, in this way, in order to improve the reliability of the outsourcing process.

Furthermore, as shown in Fig. 7b, the percentage of new services from new providers is larger than 0.9, which means that the consumers prefer to hire new services from providers they have never collaborated with in the past, indicating the importance of the mechanism in the platform to help the consumers to evaluate the quality of the human services. Additionally, it can be seen that the percentage of new providers is increasing at first and then decreases. This means that at the very beginning, the consumers have the need to explore different services from different providers; then as the consumers purchase more and more human services on the platform, they can build trust with some providers. Therefore, in time, the consumers will be inclined to purchase services from the providers they trust, this includes the new services published by those providers. This reveals the importance of building long-term relationship between consumers and providers in such a human service ecosystem.

Observation 4. Consumers are able to split their tasks into sub-jobs to be distributed to different services with similar functionality, employ such redundancy to guarantee the reliability of their businesses. However, they fail to orchestrate human services with different functional perspective to solve their complex task. Additionally, consumers intend to build reputation with providers so that the providers should understand the consumers' dynamic requirement, develop their skills and build long-term relations with the consumers.

5.3 Emergence of Service Collaboration

Q3.1: What is the emerging pattern for service cooccurrence?

In this paper, service collaboration refers to the scenario that more than one services are used together by the same consumer in a one-month time frame. Considering the sequence of the services purchased by the same consumer c_k in t_j, we can get the orchestration log as: $ols_i = \{s_{i,1}, s_{i,2}, \ldots s_{i,n_i}\}, s_{i,m_i} \in OS(c_k, t_j), m_i = 1, \ldots, n_i$. Here the order of s_{i,m_i} in ols_i represents the sequence that these services are purchased in the transaction. For example, $s_{i,1}$ is first used and then $s_{i,2}$ by consumer c_k.

Based on this definition, we can construct the homogeneity network $G_s = \{S, R_{ss} = \{r_{ss} = <s_i, s_j, w_{ij}>\}\}$ where each node s_i represents a human service, each edge r_{ss} represents the collaboration between two services s_i, s_j, and the weight w_{ij} refers to the frequency of the service co-occurrence $<s_i, s_j>$ in the same transaction.

The above method is used to build an undirected network consisting of 80,035 service nodes and 1,275,526 co-occurrence edges. Given the fact that for any service, there usually exists multiple similar services compete with each other, it is not surprising that the re-use rate for each service pair is not high. As shown in Fig. 8a the long-tail power-law distribution indicates that: during our study period, 89.47 percent of services pairs identified only occurred once, but there are a few service pairs that are purchased very often. For example, the service pairs with the maximum weight 328 are *"I will create and design a Resume, Cover Letter or LinkedIn page"*[9] and *"I will edit your complex resume, cover letter or LinkedIn"*[10], both offered by provider *"Boomsa"*[11]. However, as shown in Fig. 8b if we consider the number of unique services a service ever collaborates with, the distribution becomes very different comparing with the web services [18], [28], only 10.64 percent collaborate with just one other service while 40.39 percent services work with 2 to 10 other services. The service *"I will skyrocket your Google Rankings with 30 PR9 High Pr Seo Social Backlinks"*[12] is the most flexible one, which has been used together with other 3,971 different services. This is another indication of the fact that the collaborations among human services are much more flexible than web services as they are collaborated with each other based on the consumers' orchestration.

Furthermore, for each co-occurrence edge $<s_i, s_j>$, we can identify its collaboration type based on whether they belong to the same sub category or root category:

- *Same Sub-category Composition* uses services belonging to the same sub-category to work on the project(s).

9. https://www.fiverr.com/boomsa/create-a-new-resume-or-cover-lett er-to-ensure-an-interview-1200-feedback
10. https://www.fiverr.com/boomsa/do-extra-resume-editing-for-your-complex-resume
11. https://www.fiverr.com/boomsa
12. https://www.fiverr.com/blboss/do-pr9-high-pr-backlinks-safe-google-dofollow-quality

TABLE 3
Collaboration Among Human Services

	All Edges		Top (Edge Weight >10)	
		Same Provider		Same Provider
No. of Edge	1,275,526	29,788	4,673	612
No. of co-occurrences	1,589,485	61,139	88,933	11,643
Same Sub Category	474,164	31,680	56,381	5,754
Cross Sub Category	469,722	23,011	29,083	5,527
Cross Root Category	645,599	6,448	3,469	362

Since matching capabilities are provided in those services, a plausible scenario for this case is to divide a single task into pieces which will be distributed among all the service providers for better performance.

$$s_i \rightarrow sc = s_j \rightarrow sc. \tag{22}$$

- *Cross Sub-category Composition* uses services in the same root-category but in different sub-categories. Similar capabilities are provided by the services, a likely scenario for this case is to hire providers to develop related but different aspects of the project(s).

$$s_i \rightarrow sc \neq s_j \rightarrow sc, s_i \rightarrow rc = s_j \rightarrow rc. \tag{23}$$

- *Cross Root-category Composition* uses services in the different root-categories. In this case, very different capabilities are provided by the services. A likely scenario is that the project is highly complex and providers are hired to tackle different parts of the same project.

$$s_i \rightarrow rc = s_j \rightarrow rc \tag{24}$$

Additionally, based on the providers the two services belong to, we also consider the collaborations between the same providers:

- *Same Provider Composition* compose services provided by the same provider. A likely scenario here is that the consumer hires the same provider for different components of the project(s).

$$s_i \rightarrow p = s_j \rightarrow p \tag{25}$$

In order to delve deeper into this topic, we also computed the distribution of the edges with weight no less than 10. As reported in Table 3, it can be seen that:

- The top (4,673/1,275,526=) 0.37 percent edges with edge weight no less than 10 account for (88,933/1,589,485=) 5.6 percent of all the occurrences of the edges.
- For the whole service co-occurrence network, (61,139/1,589,485=) 3.85 percent of collaborations are between services provided by the same provider; if only consider the top edges, it becomes (11,643/88,933=) 13.1 percent.
- The distributions of the different types of edges in the whole network are surprisingly even. (645,599/1,589,485=) 40.62 percent edges are cross root category edges and then (474,164/1,589,485=) 29.83 percent are the same sub category edges. However, for the top edges, only (3,469/88,933=) 3.9 percent are the cross root category edges while (56,381/88,933=) 63.40 percent belong to same sub category.

Therefore, it seems that in overall, the chances of two random services to be composed together are the same, leaving us most of edges appearing only once in the data. This is the result of random attempts of the customers which embody little orchestration strategy. However, as time goes by, the preference attachment mechanism to reuse the service pairs results into the power-law distribution of the edge weight and some emerging patterns for the service collaborations. Specially, for these top edges, the customers have a strong tendency to compose services with the same or related functionality, or services provided by the same providers.

Observation 5. Unlike web services, human service collaborations are much more flexible. The preference attachment mechanism in service pairs reuse results into some emerging collaboration patterns, especially for the human services with the same or related functionality, or provided by the same provider.

Q3.2: What is the emerging pattern for skill collaboration?

The correlations between different sub categories can represent the relations between different human skills as well as the patterns in the consumers' requirements. Hence, we take the sequential order of the collaboration into account, from the orchestration data, and then match each service into its sub category and construct a directed edge between two sub categories if a service in each category is used successively in the orchestration. We further remove the self-connected edge and finally get the sub category network to represent how different human skills collaborate with each other to solve complex task. Note that the collaboration between different sub categories can be modeled as a directed network $G_{sc} = \{SC, R_{sc} = \{r_{sc} = <sc_i, sc_j, w_{ij}>\}\}$ where each node sc_i represents a sub category, each edge r_{sc} represents the collaboration between two sub categories sc_i, sc_j and the weight w_{ij} refers to the frequency of the sub-category collaboration pair $<sc_i, sc_j>$. The direction refers to the sequential order of two skills.

We found that Fiverr.com shows the exact comment date only for the service transactions happened in the past 30 days. Therefore, only these (46,237) services and their (124,347) transactions are used to understand the skill collaboration from the consumers' perspective. Fig. 9 reports the network diagram only considering the top 10 percent most popular edges. Each node represents a sub-category, the color refers to the type of root category, and the directional edge represents the collaboration between the sub categories while the direction means the sequence between two sub categories. The size of the node reflects the in/out degrees of the node: the bigger the node is, the bigger the number of other nodes it is connected to via in/out edges. Apparently, some root categories are more popular than the others, for example, the root category *"Graphics & Design"* indicated by yellow nodes are very popular during our study period. In fact, the top 10 percent most popular edges only include nine root-categories (81 percent) and

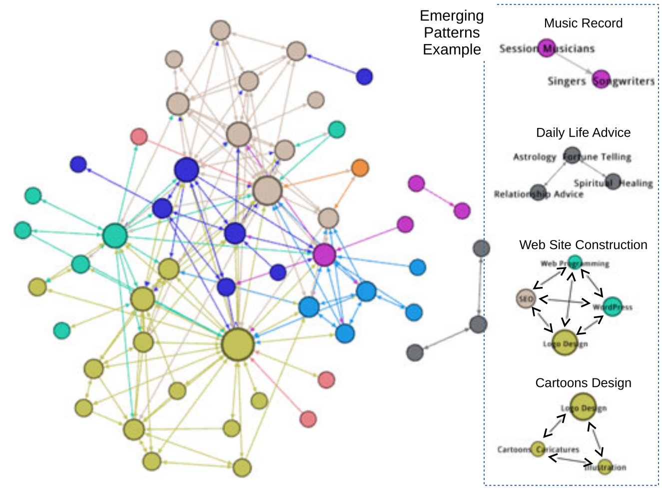

Fig. 9. Human skill collaboration patterns.

	Consumer	Provider	Platform
Q1: Provision Capability Growth		O1: Provision capability is growing O2: same sub category → cross sub category → cross root category	O1: Learning Curve for Provision is quite long
Q2: Orchestrating capability growth	O3: Orchestrating Capability is growing O4: Use redundancy to guarantee reliability	O4: Reputation and Long-term relations are important; understand the consumers' requirement and develop new services	O3: Consumers fail to continuously develop new requirement O4: Consumers fail to collaborate services for complex task solving
Q3: Emergence of Collaboration	O5: Human services are more flexible for composition; Preference attachment mechanism for service pair reuse	O6: Human skills collaborate are not random but emerges patterns for complex task	O5 & O6: Collaboration between human services is the emergence of human's cognitive

Fig. 10. Inspirations for adoptions of human services.

52 sub-categories (49 percent). This implies that the excluded root/sub-categories are not often used in the compositions. Additionally, it can be seen that most of the collaborations happen between the sub categories belongs to the same root category, which is consistent with the observations above. It also somehow proves the effectiveness of the functionality organization in the platform.

An interesting observation here is that we can spot quite a few intuitive collaboration patterns in the network graph. For example, as shown in the upper right of Fig. 9, the "*Session Musicians*" and "*Singers Songwriters*" pattern emerges for music record; services from "*Relationship Advice,*" "*Astrology Fortune Telling*" and "*Spiritual Healing*" are used together for daily life advice. "*Logo Design,*" "*Cartoons Caricatures*" and "*Illustration*" can be purchased together to finish the cartoons design task. If the consumer needs to construct a web site, the services from "*SEO,*" "*Web Programming,*" "*WordPress*" and "*Logo Design*" crossing the root category "*Graphics & Design,*" "*Programming & Tech*" and "*Digital Marketing*" are necessary. Apparently, these emerging patterns can be used to help the consumers to solve complex tasks and help the providers to deliver new services.

Observation 6. The relations among human skills are not random and some patterns emerge over the service collaborations, which can be used to solve complex tasks and suggest skill development.

6 Adoption Strategy

The empirical study about the Fiverr.com has uncovered the development patterns in the human service ecosystem, which can offer us many inspirations for the further researches from the perspectives of many different disciplines, including computer science, software development, economic and management science. Here, we organize our empirical observations from the provider, consumer and platform perspective. As reported in Fig. 10, we can identify the following three potential applications of the patterns discovered in this study.

6.1 Service Recommendation for Consumers

Service recommendation, suggesting the "right" services to fulfill the consumers' request, is a promising methodology to help the consumers to solve the information overload problem [17]. As shown in Section 5.2, we can observe that the consumers' orchestration capability grows as they complete more transactions in the platform. Some researchers begin to consider exploiting the growth patterns of web service composition, like the topic evolution [33], to improve the recommendation performance. However, there are rooms to further facilitate the consumers' human service selection in the platform. For example, our empirical study shows that consumers are able to purchase more services in a transaction so that it is reasonable to offer more candidates for those consumers who are more adept. Additionally, some consumers intend to split their tasks into different sub-jobs so that they can use the redundancy to guarantee the reliability of their businesses considering the uncertainty of human services. Therefore, offering similar services from the same sub category is a good strategy when generating recommendations for these consumers.

Furthermore, consumers intend to build trust with the providers based on their collaborations as the human services are more flexible and their collaborations are based on human communications. This means that long-term relationship and trust is extremely important. New services from the trusted partners are more preferred and this trust mechanism can be exploited to improve the performance when recommending new services [32].

In addition, our observations show that although the consumers become more proficient over time, they still fail to develop more new requirements in the platform in the long run. One reason is that, in general, consumers and providers both view the human service platform as a marketplace for temporal jobs [45], [51] and they are reluctant to heavily rely on such marketplaces to outsource complex projects. Therefore, how to help the consumers split their complex task and orchestrate complex services for reliable problem solving is one important and valuable research question. In addition, how to understand the consumers' requirements and help them develop new requests is also important for the booming of the human service ecosystem.

Adoption 1. *It is valuable to consider the capability growth pattern to improve the performance of service recommendation for consumers. Since the human services are much more flexible than web services in terms of interoperability, it is important to understand the consumers' requirements and then help them* *to collaborate services for complex task solving. This is a critical mechanism which can drive the growth of the ecosystem.*

6.2 Skill Development Assistant for Providers

Providers are the "soil" for the growth of the human service ecosystem. Our observation shows that the ever provided services/sub category/root category are all increasing as time goes by. The providers indeed become more professional for service provision as they stay longer in the platform. However, it can be seen that the ever provided services per provider is still less than 4, the ever provided sub category is no more than 2.5 and the ever provided root category is only 1.526. More importantly, the current learning process is about 8 months, which is too long for such a platform. This is consistent with the argument that service providers are disincentivized from learning new sub categories (skills) [45], [50]. Though some mechanisms like reputation transferability [51] and "micro-internships" [51] had been developed to assistant the provision development process, how to guide service providers to effectively grow their provision capability remains unclear.

One key observation is that, the consumers tend to purchase new services from the providers they ever collaborated with in the past. Therefore, the providers should try to build long-term partnership with the consumers and continuously develop new services to fulfill the consumers' new requirements. Additionally, it is easier for the providers to develop new services in the same sub category (aka, the same skill), and then the cross sub category belonging to the same root category (aka, the same human service domain). Developing new services in a different root category is much more difficult. It is important to develop a strategy which can be used to guarantee the effectiveness of the skill expansion.

The collaboration patterns identified in the sub category collaboration network reveals that the relations among human skills are not random. On the contrary, the emerging patterns indicate the latent relations among these skills. In other word, the skills requested by consumers are inherently related with each other, which can be used to help the providers develop the new skills that are in high demand in the ecosystem. Thus, it is promising to provide effective long-term career development for providers [12] and increase the sustainability in the human service ecosystem.

Adoption 2. *Developing assistant tools and mechanisms to reduce the learning curve for provider and help them to extend their skills based on the emerging skill patterns. This is a promising and important application to facilitate the effective growth of human service ecosystem.*

6.3 Systematic Support for Platforms

The platform is the market place to enable the mapping between human services and consumer requirements, which is the core function of such two-sided markets [52], [57], [58]. Our empirical study discover similar learning curves with a "diminishing marginal utility" and then "increasing marginal utility" for both the growth of the provision capability and orchestration capability. However, the learning curve for consumers is much shorter than the providers. It is reasonable because the consumers are the users of the platform where many approaches have been developed to facilitate effective task assignment or service recommendation [17], [38], [42], [59]. However, the growth of the service provision is also indispensable to enable the network effect [52], [57] for such two-sided market and mitigate the imbalance between the supply and demand of human services. Therefore, *the platform should pay more attention to the service provision side to support the human service development*.

Most of the collaborations occur in the "same sub category" type, which is motivated by the limitation of human services' capability as well as the requirement for work reliability. However, due to the complexity of the business process, in most cases, different services with different functionality are required. *This gap indicates an urgent demand to support the compositions between different types of human services to solve complex requirements*. Actually, our empirical study shows that the consumers fail to orchestrate complex human services and continuously develop new requirement to use new services. How to inspire the consumers to keep developing new requirements is important to increase the platform's stickiness.

Finally, although the human services are much more flexible than the web services, the preference attachment mechanism is extremely significant for the reuse of trusted services. Also, the collaborations among different human skills are not random but exhibit some clear orchestration patterns. These observations indicate the advanced cognitive and social abilities of humans during collaboration. Therefore, building the multi-agent model to delve deeper into the interaction among human services is necessary for the platform to understand the human's cognitive.

Adoption 3. *The platform should pay more attention to reduce the providers' learning curve, and develop new tools to enhance the collaboration among different human services so that consumers can conveniently and reliably utilize skill compositions to solve their complex tasks.*

7 Conclusions

Triggered by the crowdsourcing strategy and the development of human services, human service ecosystem has been growing rapidly in the recent years. In this paper, we have developed a quantitative model to understand the evolution of the human service ecosystem, with a focus on the growth of service provision and orchestration capability, as well as the emerging patterns of human service collaboration. Our empirical study based on the prominent human service platform, Fiverr.com reveals the two major differences between web services and human services: human service provision and orchestration capability are not static but growing; human service collaboration is more flexible while some skill collaboration patterns emerge through service orchestrations by consumers. Based on our observations, we have identified the following three promising adoptions for further human services adoption and research:

- *For consumers*, the growth of consumers' orchestration capability can be utilized to improve the quality and performance of service recommendation. Most importantly, tools to help consumers to collaborate in different human services for complex task solving are indispensable.

- *For providers*, reducing the learning curve and continuously developing new services as a long-term "career" are the fundamental requirements to enhance the provision capability.
- *For platforms*, digging into the service collaboration patterns is important to understand the emergence of the human cognition so that the platform can support new mechanisms to facilitate the growth of the ecosystem.

Though the results are constrained within a given online labor market, the Fiverr.com, the presented model and methodology are applicable for other marketplaces, like Upwork or Freelance. We plan to examine our extracted patterns in those platforms to verify their generosity. More importantly, our project has opened a gateway for many interesting future directions to facilitate the human services adoption from both the service computing and crowdsourcing perspective. For example, this study reveals the emerging patterns among skills from service orchestration perspective, which provides some in-depth understanding of the skill relations from both supply side and demand side. In addition, we plan to develop a recommendation framework suggested in Section 6 to optimize the decisions for service providers, consumers and platform operators.

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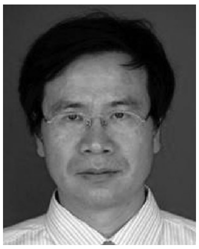

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