System Dynamics Modelling to Study the Diffusion of a Supply Chain Management Mobile Application

Anna C. Cagliano, Alberto De Marco, and Carlo Rafele

Abstract— The local fresh food supply chain is experiencing market fragmentation and little coordination among suppliers and customers, which demand for integrated management by means of a timely information exchange connecting all the supply chain echelons and enabling efficient logistics activities. Mobile communication technologies can support the achievement of such goals because of their large diffusion and ability to ensure real time information updates. In this context, a System Dynamics model is developed to study the diffusion pattern and the associated operational and economic impacts of a new application for mobile devices assisting supply chain operations. A fresh food supply chain in Northern Italy has been considered. The base application and the integration of three additional features allowing the management of product traceability, electronic payments, and time-sensitive deliveries are investigated. Simulation results provide an understanding of the mechanisms of adoption of the mobile services and help define business policies to disseminate their diffusion.

Keywords— Bass model, innovation diffusion, local fresh food, mobile applications, supply chain management, System Dynamics.

I. Introduction

THE introduction of micro-browsers and similar applications in wireless communication devices gives the possibility of having the Internet “in one’s pocket” and of performing a variety of activities without being in front of a computer [1], [2]. The development of such technologies changes not only business environments but also selling and purchasing processes [3], [4], [5]. In particular, mobile devices such as smartphones and tablets connected to the Internet can purposefully support supply chain management (SCM), from placing orders to delivering products, as well as making the associated decisions. This is of great value to the logistics industry because the strategic use of wireless and Internet technologies may drive business innovations, increase the customer service level, and eventually secure competitive advantage and long term profits [6], [7].

Some industries, especially those poorly structured and involving a great number of players, are characterized by a scarce control on the information flow among supply chain (SC) partners and sometimes by a lack of an appropriate physical logistics connected to delivery. In such contexts mobile technologies play a significant role because they can improve purchase transactions and the physical distribution process. Also, they can enable the use of electronic communications for more than simply placing orders. Finally, they can support a re-engineering of the logistics process by connecting all the SC members with real time information.

This paper focuses on local fresh food, a sector suffering from the drawbacks just discussed being characterized by a myriad of small producers and retailers as well as of consumers that often operate without any kind of SC coordination [8]. In the literature several contributions do exist analyzing how electronic and wireless communication innovations can purposefully support the fresh food industry, and in particular the associated SCs. However, such works mainly focus on the point of view of final consumers and pay little attention to the other SC echelons and how they interact with one another. Also, they are usually ex-post survey-based studies and not preliminary feasibility analyses. Furthermore, very few studies are concerned with local SCs of fresh food.

In order to contribute to overcome this research gap and provide a comprehensive understanding on the behavior of all the SC partners, the System Dynamics (SD) modelling and simulation approach has been applied to study the benefits and the potential diffusion of a novel application for mobile devices facilitating and integrating the SCM from order to delivery. To this end, a reference local fresh food SC based in the city of Torino, Italy, has been considered. The results of the simulation model show the advantages of the application and allow designing some policies for stimulating its diffusion. The paper is organized as follows. An overview of the literature forming the theoretical background of this work is presented in Section 2. Section 3 details the methodology, while Section 4 describes the SD model as well as the associated simulation results. Section 5 discusses policy making. Section 6 introduces benefits and limitations of the analysis, implications, and future research directions. Finally, conclusions are given in Section 7

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II. Literature Background

The present work is grounded in two main streams of literature. The first one is concerned with the contributions about electronic and mobile technologies applied to the fresh food SC. The second one deals with the theoretical pillars supporting the development of the SD model, namely innovation diffusion analysis, with particular regard to the Information and Communication Technology (ICT) area, and SD applications to SC issues. Each of these streams will be discussed in the following sub-sections.

A. Applying Electronic and Mobile Technologies to the Fresh Food Industry

Electronic and mobile technology implementations in the fresh food SC are mainly associated with electronic grocery (e-grocery), which is one interesting application of the wider concepts of electronic and mobile commerce. E-grocery allows ordering groceries from home in an electronic way and in most of the cases the products are then delivered directly at one’s house [9].

There is quite a consistent body of literature discussing e-groceries and the associated benefits. A number of authors analyze the main factors that lead consumers to buy groceries online. Such aspects include the possibility of doing shopping at any hour without visiting a retail store, the wide range of the available products and of the associated information, the price, and the influence of “word of mouth” [10], [11], [12], [13]. Other contributions use surveys to investigate the consumer response to and demand for online food retail channels [14], [15]. Additionally, some works identify the characteristics that impact on the rate of adoption of e-grocery: among them the perceived relative advantage compared to traditional retail stores and the perceived possibility of trying an innovation without huge investments can be mentioned [9], [16]. Finally a number of publications also deal with the structures, costs, and service levels of the distribution processes of companies selling food online [8], [17], [18], [19] as well as with the associated inventory costs [20]. Particular attention is given to the grocery sector.

B. Theoretical Pillars of the System Dynamics Model

This part of the literature review aims to understand the possible diffusion paradigms that are available to represent the dynamics of growth of the users of the new mobile application. Also, it is intended to analyze previous applications of SD to SCs that can guide the development of the model discussed in the present work.

Analyzing Innovation Diffusion

When studying trends of innovation growth, the S-shaped pattern is very frequently used in order to represent the spread of innovations. At the beginning, a limited number of users, named “innovators”, adopt and form that critical mass that will play a key role in the subsequent diffusion process. Then, other users, defined as “imitators”, will adopt as a consequence of the social interaction with the innovators and of external factors such as advertising. The demand for the innovation first increases and meets its maximum value and then it decreases and equals zero when the market saturation point has been reached. Therefore, the curve of the cumulated number of adopters grows rapidly when the demand for innovation is rising and then increases at a slower rate while approaching the market saturation [21], [22].

Numerous models to forecast innovation diffusion do exist, among them the Gompertz, Logistic, Bass, and Fisher-Pry models [23], [24].

In particular, the Bass model [25] has been used in very heterogeneous fields such as retail services, industrial technology, agricultural, educational, pharmaceutical, and consumer durable goods sectors, being it quite intuitive and simple but, at the same time, with a high power of demand forecasting [26]. The Bass model has been extensively applied in the ICT arena too. Its original formulation and subsequent extended versions are suitable to model the timing of the process of the adoption of a technology, tightly dependent on the innovation aptitude of each class of potential adopters [27]. The Bass model has been implemented to study the diffusion of mobile telephony and communication infrastructures as well as to forecast the demand of mobile communication services [22], [28], [29]. With the aim of capturing the complex cause and effect relationships among the factors involved in the diffusion of an innovation in the ICT field, some contributions rely on the SD representation of the Bass model provided by Sterman [30] to develop frameworks for identifying the economic and socio-cultural determinants affecting the capacity to adopt ICT innovations, defining policies to stimulate the diffusion of ICT solutions, or forecasting the success of products either prior to their launch or during their lifecycle [31], [32].

Supply Chain Modelling with System Dynamics

SD is a mathematical modelling and simulation approach aimed at understanding the behavior of a complex system to support policy design. This methodology enables to graphically represent a system of interrelated stock, flow, and auxiliary variables, define the mathematical equations describing the relationships among them, and perform a computer-based simulation to determine the trends of the investigated variables over a preset period of time. Model validation is performed through historical data and sensitivity analysis. Main references for the SD methodology are [30] and [33]. For a quick summary of the SD approach as well as a sample application, the reader can also refer to [34].

Sterman offers a very detailed SD representation of a SC [30]. Based on his work, contributions focus on several issues affecting both manufacturing and service industries [35], [36], [37]. SD has been applied to capture the interrelation between SC responsiveness and efficiency and to study the effects of strategies to improve them [38], [39]. Furthermore, SD models have been developed to examine instabilities in the SC due to actions addressing the imbalances between supply and demand like price changes, promotions, and the involvement of additional suppliers [40]. SD proved to be beneficial in SC reengineering and to characterize the conditions under which the bullwhip effect can occur [41]. Finally, SD models have been extensively used to evaluate the operational and economic performance of SCs [42], [43].

The literature review highlights several findings. First, while numerous works focus on e-grocery, the issue of how local fresh food SCs can benefit from electronic and mobile technologies is seldom addressed. Also, research on e-grocery mainly takes the final consumer perspective, without considering the other SC partners, such as retailers and producers, and the degree of the interactions among them. However, e-commerce and mobile commerce technologies show their greatest application potential with the transactions involving B2B partners [44]. Furthermore, contributions about the diffusion of e-grocery and of the supporting mobile services are usually ex-post studies and few publications present preliminary feasibility assessments of new mobile applications assisting SCM in the local fresh food sector.

Second, the literature review reveals that the Bass model is the best approach for analyzing the diffusion of the mobile application at issue given its forecasting power in the ICT arena as well as its numerous implementations in the area of this research.

Third, SD modelling of SCs proves the suitability of such tool for representing and understanding the dynamics of the interactions among different partners and studying the consequent emerging system behavior.

Based on such literature background, the present work combines the Bass diffusion model and an inventory management model in a single SD framework in order to preliminary assess the potential operational and economic impacts of the diffusion of a mobile application assisting in the local fresh food SCM. The mutual connections between the adoption of the service by producers, retailers, and consumers and the SC performance are investigated.

III. Methodology

In order to understand both the methodology and the proposed model it is beneficial to briefly explain the basic characteristics of the mobile application at issue. The application has two main functionalities, namely assisting SC operations and supporting vehicle routing. It enables online order placement, inventory control, dispatching and receiving management. All users share product, order, inventory, and shipment information and are charged a fee for receiving orders or dispatching deliveries by using the application. Moreover, the application can feature three optional services respectively assisting in product traceability management, electronic payments, and “time sensitive” delivery management. The adjective “time sensitive” refers to deliveries whose time window can be changed by the customer even shortly before the planned execution time. It is important to highlight that electronic payments by means of mobile devices are a promising development of mobile commerce [45].

The study has been carried out through a phased approach [46]. First, semi-structured interviews are conducted with consumers, retailers, and producers, who will be named farms hereinafter, to create a knowledge base on the industry processes. The interviews also identify a clear willingness of the SC players to adopt the service and provide quantitative data for running simulations. Then, a simple SD model is designed to capture the most important flows, state variables, and feedback loops. Finally, a detailed SD model is calibrated and simulation results are analyzed. Comparisons between the diffusion trends of the base application and those resulting from also adopting the optional features are made. The Bass model has been used given its suitability to represent the dynamics of diffusion of ICT-based and mobile services.

The reference market is composed of producers, retailers, and consumers of fresh food in a target urban area of 1.5 million population in the greater Torino area, Italy.

IV. Model Development and Simulation

This section details the SD model and the simulation results. Main aspects of the model will be here discussed. The complete list of the associated equations is available from the authors.

A. *The System Dynamics Model*

The SD model is structured into ten interconnected sub-models concerned with the diffusion of the base application among consumers, retailers, and farms, order issuing, inventory management, user satisfaction, the revenue for the service provider company, and the diffusion of the three optional features (Retailer Technology Adoption, Farm Technology Adoption, Time Sensitive Delivery Adoption, and NFC Payment Adoption sub-models) (Fig.1). The studied SC includes those actors relying on the mobile service for both placing orders upstream and delivering goods downstream. Also, users may adopt as a consequence of either advertising or “word of mouth”. Advertising is performed by both the suppliers that have already adopted the mobile application, through verbal persuasion of their customers to use it because of its efficiency and easiness of use, and the service provider company, by means of formal campaigns. “Word of mouth” is pursued by adopting customers towards their suppliers and between members of a same SC echelon. This second implicit form of “word of mouth”, which basically consists in observing the behavior of a competitor, is named emulation.

The model is based on Sterman’s [30] representations of the Bass model and of a manufacturing SC and has been developed using the Vensim DSS software package. The simulations have been performed with Euler integration, with one-day time intervals and a simulation horizon of 156 weeks corresponding to about 3 years.

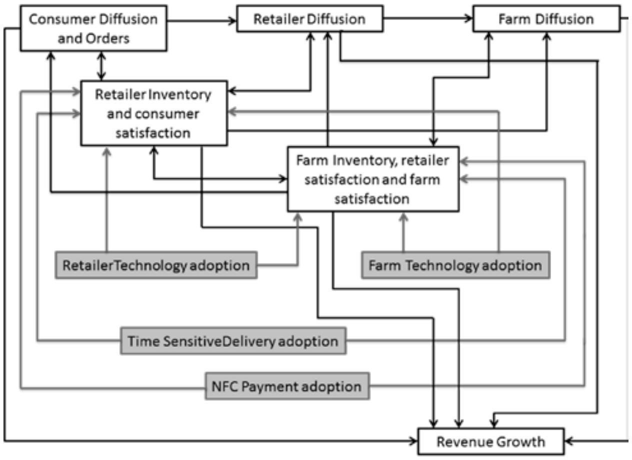

Fig.1 Model Overview

The SD model presents many feedback loops among variables. Some basic examples of feedback loops governing the diffusion are here detailed. A growth in the number of consumers adopting the mobile application increases the order rate to retailers and how successful these players are in fulfilling the augmented orders determines the consumer satisfaction. Satisfaction, in turn, influences the growth of adopting consumer population through the “word of mouth” effect. A similar situation can be observed for retailers and producers. Also, all the other variables remaining equal, a growing number of retailers adopting the mobile application makes the orders to the farms increase, which in turn makes the order rate to each single farm go up. The possible increase in the business volume as a consequence of the use of the new application is perceived by the retailers that are stimulated to further adopt. The more the adopting retailers the more effective their “word of mouth” action on farms that results in an increased number of adopting farms. As the total number of farms goes up, the order rate faced by each single farm, that is her business volume, tends to be limited. This makes the persuasion action of farms towards retailers decrease and as a consequence the number of retailers adopting the mobile application grows slowly. Finally, the more the adopting farms, the more the products available to retailers, and the higher the retailer satisfaction. Such satisfaction with the use of the mobile application makes the “word of mouth” action of retailers towards farms be more effective and thus the number of adopting producers increases.

Consumer Diffusion and Orders

Fig.2 shows the variables and the relationships among them determining the dynamics of the diffusion of the base mobile application, without including any optional features, among consumers. The stock variable “Potential Consumers”, representing all the consumers that might adopt the application, is decreased by the flow of the consumers actually adopting the application, represented by the variable “Consumer Service Adoption Rate”. The latter in turn increases the stock variable “Consumers” that models the number of users of the application.

According to the Bass diffusion model, consumers may adopt as a consequence of either advertising or “word of mouth” [25]. The equations of the associated portion of the SD sub-model are inspired by Sterman [30]. The number of adopting consumers, together with the average number of orders per consumer in each single time step, determines the “Consumer Order Rate” which feeds the stock “Consumer Orders”. The SD model is based on a standard order composition and does not consider the variability of the products that form an order.

The key equations of this sub-model are:

Potential Consumers = INTEG (− Consumer Service Adoption Rate, Total Consumer Population) (1)

Consumer Service Adoption Rate = max (0, Consumer Service Adoption from Advertising + Consumer Service Adoption from Word of Mouth) (2)

Consumers = INTEG (Consumer Service Adoption Rate, 1) (3)

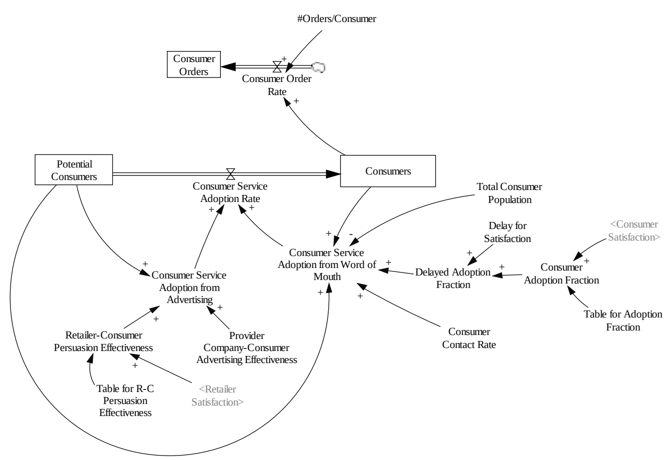

Fig.2 Consumer Diffusion and Orders

Retailer Diffusion

This sub-model is very similar to the one discussed in the previous sub-section (Fig.3 and Fig.4). However, the equations defining the adoption from both “word of mouth” and advertising have been modified to take into account the different ways a retailer can be induced to use the application.

“Word of mouth” actions are performed by the adopting consumers towards the retailers through description of the efficiency and ease of use of the application. Additionally, they can be in the form of emulation: one retailer observes the benefits given by the application to her competitors. Thus, the variable “Retailer Service Adoption from Word of Mouth” is calculated as per equation (4):

Retailer Service Adoption from Word of Mouth = Consumer-Retailer Word of Mouth Adoption + Retailer-Retailer Emulation Adoption (4)

Advertising actions perceived by retailers can come from both formal campaigns sponsored by the service provider company and the persuasion of farms who will try to convince retailers to adopt the application because of its performance. The variable "Retailer Service Adoption from Advertising" is calculated as:

*Retailer Service Adoption from Advertising = Potential Retailers * (Farm-Retailer Persuasion Effectiveness + Provider Company-Retailer Advertising Effectiveness)* (5)

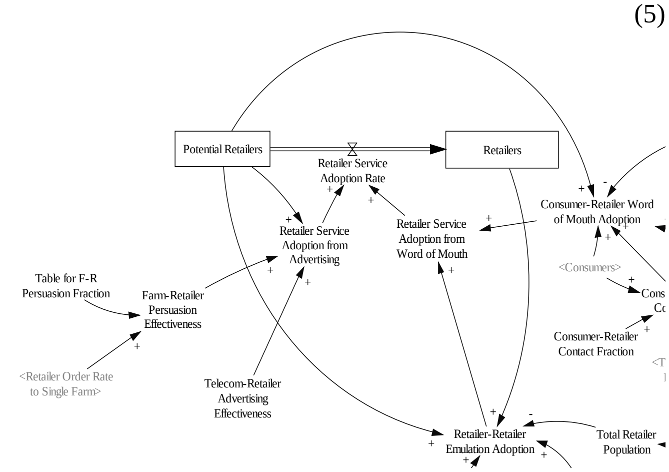

Fig.3 Retailer Diffusion (a)

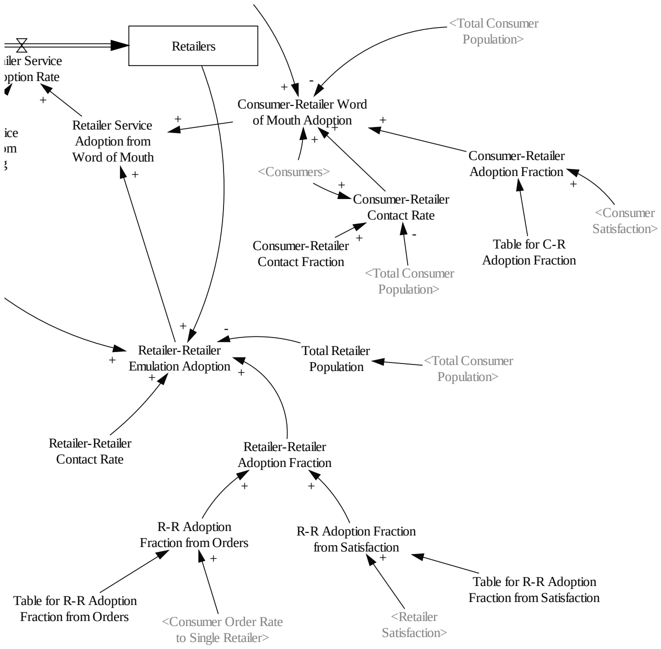

Fig.4 Retailer Diffusion (b)

Retailer Inventory and Consumer Satisfaction

As far as the inventory management of the retailer is concerned (Fig.5), the stock variable "Single Retailer Inventory" is augmented by the flow of orders received from farms by each single retailer ("Single Retailer Receiving Rate") and diminished by the flow of orders shipped to consumers ("Single Retailer Shipment Rate") according to equation (6):

Single Retailer Inventory= INTEG (Single Retailer Receiving Rate − Single Retailer Shipment Rate, 40) (6)

The consumer demand determines both the shipment rate, according to the number of orders that can be fulfilled from the stock, and the orders to the farms based on a forecast of future consumer orders modelled as a first-order exponential smoothing of the present order rate.

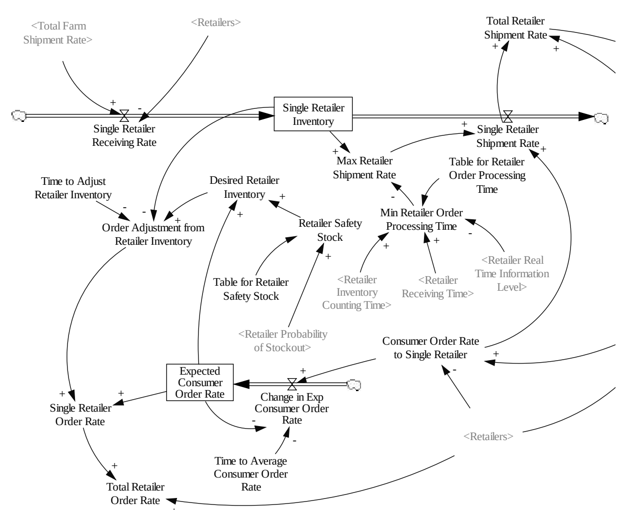

Fig.5 Retailer Inventory Management

In order not to excessively complicate the model, consumer satisfaction has been calculated as a global value taking into account both those consumer adopting the base application and those ones also using the additional features. In the case of consumers, just the payment management service relying on the Near Field Communication (NFC) technology applies (Fig.6). Thus, consumer satisfaction is determined as per equation (7):

*Consumer Satisfaction = Consumer Receiving Service Level * (1−Weight of Pricing) + Consumer Sensitiveness to Pricing * Weight of Pricing* (7)

The service level associated with the use of the mobile application ("Consumer Receiving Service Level") is defined by "Consumer Order Fulfilment Ratio", which measures how many orders are fulfilled in every time step, "E-Order Service Reliability", which assesses the degree of reliability and security of the electronic system to place orders, and "Consumer Receiving Timeliness and Efficiency", which evaluates the efficiency of receiving goods with the support of the mobile SC service. The contribution of the payment management feature to the service level perceived by consumers depends on the number of retailers adopting such payment system. Also, the more the consumers actually using it, the more the influence on the global degree of satisfaction.

The variable "Consumer Sensitiveness to Pricing" compares the price expected by consumers with the actual one. In addition to the "Receiving Unit Fee" and the "Dispatching Unit Fee", each SC member is charged with the "WebApp Unit Price" in order to download the application allowing using the services.

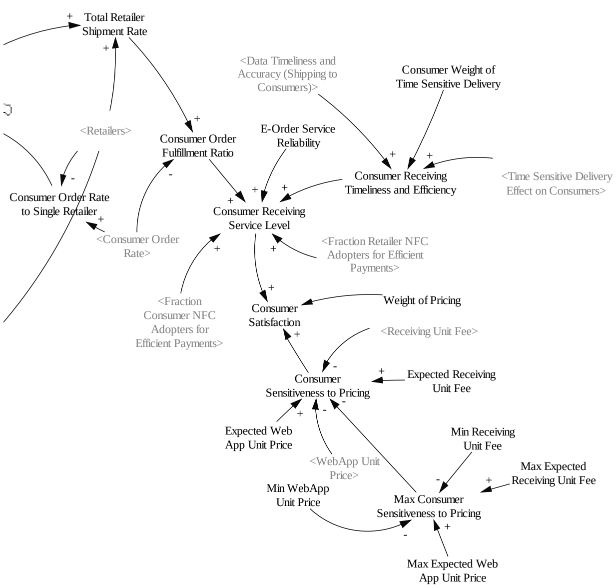

Fig.6 Consumer Satisfaction

The sub-model about farm inventory, retailer satisfaction, and farm satisfaction is very similar to the one discussed in this section.

Farm Diffusion

The dynamics of the diffusion of the base application among farms is similar to the one discussed for retailers. In the present case the adoption from "word of mouth" is determined by both the action of retailers towards farms and the emulation of adopting farms by those producers who have not adopted the application yet. The adoption from advertising is a consequence of the campaigns sponsored by the service provider company.

Retailer Technology Adoption

This sub-model explains the diffusion among retailers of the optional feature concerned with product traceability. Such additional service offered by the application is based on a traceability system relying on Radio Frequency Identification (RFID) technology. NFC could also be used as an alternative to RFID. The service is intended for SC players managing an inventory: retailers and farms.

Let us focus on retailers (Fig. 7 and Fig.8). The more retailers adopt the product traceability system the more the quantity of information available real time in the SC, due to the acquisition of the information contained in the RFID tags that enables a better management of both stocks and deliveries [47]. The increase in the level of information creates a number of benefits, such as a reduction in the order fulfilment time, a decrease in the inventory counting time [48], and less time spent on receiving goods [49]. The last two advantages give in turn more time available to process orders and contribute to further decrease the order processing time. Additionally, an improved information environment determines a reduction in the probability of stock-out, which brings as a consequence a lower level of safety stock [48]. Such aspects reflect on a more efficient inventory management and an increased shipment rate, as shown in Fig.5. The relevant equations governing this mechanism are the following:

Single Retailer Shipment Rate = max (0, min (Consumer Order Rate to Single Retailer, Max Retailer Shipment Rate)) (8)

Max Retailer Shipment Rate = Single Retailer Inventory/Min Retailer Order Processing Time (9)

The increased possibility of fulfilling order in a short time positively influences the consumer satisfaction which in turn stimulates new retailers to adopt the application as well as the product traceability management feature, thanks to the "word of mouth" effect. Moreover, the retailers will be stimulated to adopt the optional feature also though the observation of the level of satisfaction of other retailers that have already adopted it. The positive adopting trend thus created is counterbalanced by the retailers' aptitude to technology investment, which basically depends on the infrastructural costs of introducing an RFID-based product traceability system: the more such costs the less the adoption of the application feature.

The key equations of the present sub-model are:

NFC RFID Retailer Adopters = NFC RFID Retailer Adopters (T−1) + [(Retailers (T−1) − NFC RFID Retailer Adopters (T−1)) + (Retailers − Retailers(T−1))] NFC RFID Retailer Adoption Fraction* (10)

where "NFC RFID Retailer Adopters" represents the number of retailers that have adopted the traceability feature in addition to the base mobile application and "NFC RFID Retailer Adoption Fraction" models the fraction of retailers that also adopt the traceability feature in each time step T. It is worth mentioning that, according to Vensim notation, variables without the indication of the associated time step refer to the current time period. The variable "NFC RFID Retailer Adoption Fraction" is given by Equation (11):

*NFC RFID Retailer Adoption Fraction = Retailer Aptitude to Investment * Weight of Investment Cost + Retailer Satisfaction (T−1) * (1−Weight of Investment Cost)* (11)

The decision of adopting the optional product traceability feature depends on the willingness to invest in the physical infrastructure to implement the traceability system in the warehouse ("Retailer Aptitude to Investment") and on the user satisfaction in benefitting from both the base application and the traceability option ("Retailer Satisfaction"). "Weight of Investment Cost" represents the importance of the required investment cost in choosing whether adopting the feature at issue.

The Farm Technology Adoption sub-model has the same structure as the Retailer Technology Adoption portion of the SD model.

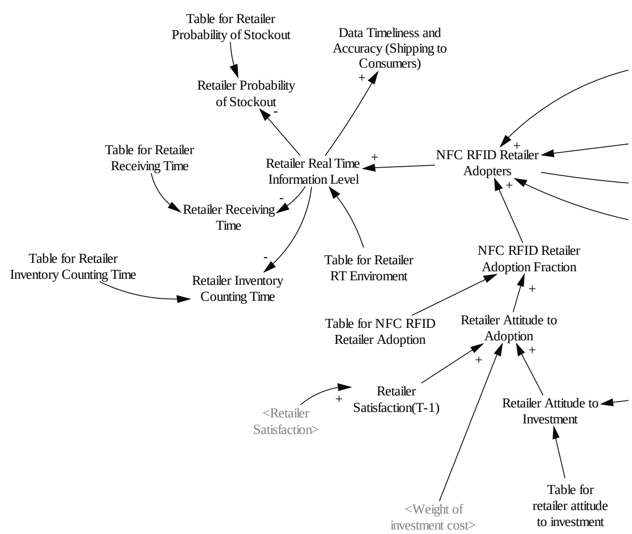

Fig.7 Retailer Technology Adoption (a)

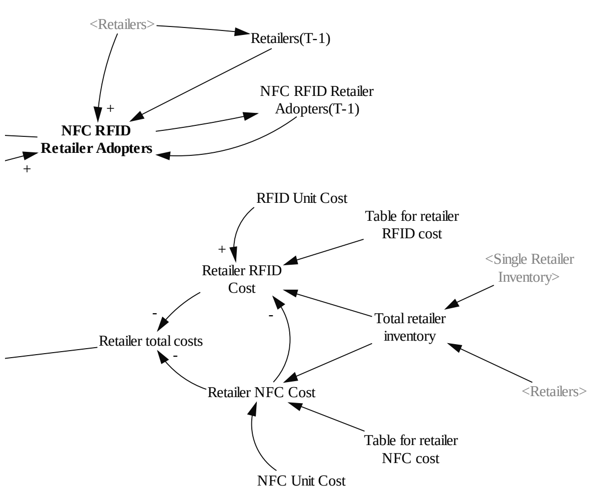

Fig.8 Retailer Technology Adoption (b)

Time Sensitive Delivery Adoption

This sub-model refers to the farms' and retailers' adoption of the application option managing "time sensitive" deliveries. Of course, consumers do not perform deliveries, so there is no need for using this feature. However, they can still benefit from "time sensitive" deliveries by retailers.

The adoption of this optional service by farms or retailers depends on the level of satisfaction of their customers, retailers or consumers, with the "time sensitive" deliveries offered by other competitors. The more their satisfaction the more they will try to convince new farms or retailers to adopt this kind of delivery. Also, the more the players offering "time sensitive" deliveries, the more their customers will be able to take advantage of such service (variables "Time Sensitive Delivery Effect on Retailers" and "Time Sensitive Delivery Effect on Consumers", see for instance Fig.6), thus increasing their degree of satisfaction with the application. The adoption is modelled as per equation (12) in the case of retailers, where T indicates the current time step:

*Retailer Time Sensitive Delivery Adopters = Retailer Time Sensitive Delivery Adopters (T−1) + [(Retailers (T−1) − Retailer Time Sensitive Delivery Adopters (T−1)) + (Retailers-Retailers (T−1))] * Retailer Time Sensitive Delivery Adoption Fraction* (12)

Similarly to Equation (10), the variable "Retailer Time Sensitive Delivery Adopters" models the number of retailers that have adopted the "time sensitive" delivery management feature in addition to the base application and "Retailer Time Sensitive Delivery Adoption Fraction" represents the fraction of retailers that also adopt the "time sensitive" delivery option in each time step. "Retailer Time Sensitive Delivery Adoption Fraction" is a direct function of the consumer satisfaction.

Fig. 9 shows the retailer portion of the sub-model. Similar considerations can be done for farms.

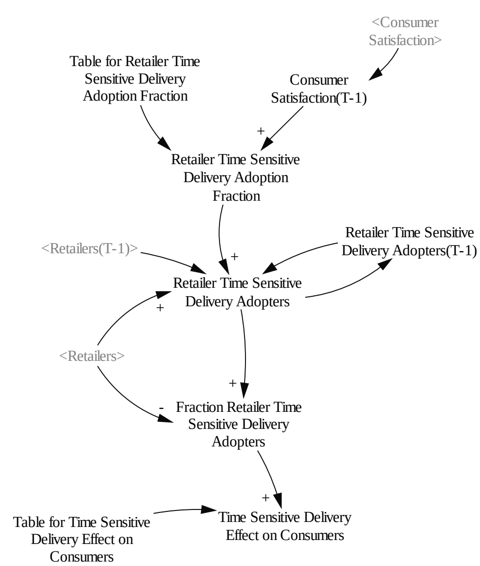

Fig.9 Retailer Time Sensitive Delivery Adoption

NFC Payment Adoption

The sub-model represents the adoption of the application option supporting payments via NFC by farms, retailers, and consumers. Their adoption in each time period is conditioned by their level of satisfaction.

Let us consider again the example of retailers, the more the retailer satisfaction with the use of the feature, the more they will encourage new retailers to adopt the application together with the payment option. Moreover, it is assumed that payments via NFC technology are completely reliable: all transactions are successful and generate satisfaction. For this reason the level of satisfaction is assumed to be proportional to the fraction of the optional service adopters.

NFC payment adoption is described by equation (13) in the case of retailers:

*Retailer NFC Adopters for Efficient Payments = Retailer NFC Adopters for Efficient Payments (T−1) + ((Retailers (T−1) − Retailer NFC Adopters for Efficient Payments (T−1)) + (Retailers-Retailers (T−1)))*NFC Retailer Payment Fraction* (13)

where again "Retailer NFC Adopters for Efficient Payments" models the number of retailers that have adopted the optional feature supporting electronic payment in addition to the base application and "NFC Retailer Payment Fraction" is the fraction of retailers that also adopt that feature in the each time step T. "NFC Retailer Payment Fraction" depends on "Retailer Satisfaction".

Fig. 10 presents the retailer portion of the sub-model. Similar considerations can be done for farms and consumers.

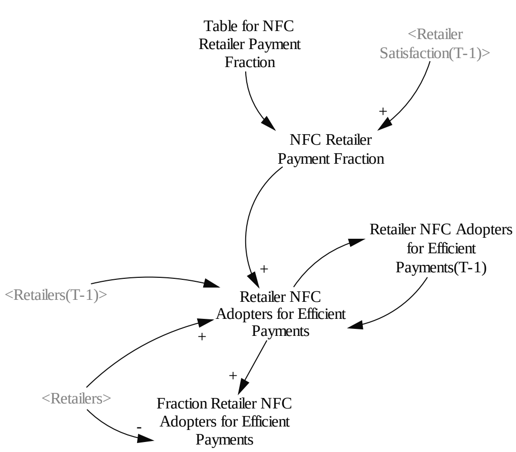

Fig.10 Retailer NFC Payment Adoption

Revenue

This sub-model evaluates the revenue for the service provider company produced by the diffusion of the mobile application and its three optional features (Fig. 11).

The revenue is calculated as the sum of the revenue from supporting the activities of receiving and dispatching orders ("Order Fees Revenue") and the revenue from selling the application ("App Adoption Revenue"). Both the weekly total revenue and its cumulated value over the simulation time horizon are computed. Being all the transactions managed by means of the mobile application charged with a fee, the optional services can be adopted by the users of the base application at no additional cost.

Following the equations that characterize the present sub-model.

Order Fees Revenue = INTEG (Revenue Rate from Consumer Receiving + Revenue Rate from Retailers + Revenue Rate from Farm Dispatching, 0) (14)

the integral is calculated over each week of the set time horizon.

The variable "Revenue Rate from Consumer Receiving" gives the revenue for the service provider as a consequence of consumers placing and receiving orders through the mobile application and its optional features (Equation (15)):

*Revenue Rate from Consumer Receiving = Total Retailer Orders Shipment Rate*Receiving Unit Fee* (15)

The variable "Revenue Rate from Retailers" measures the revenue produced by retailers receiving and dispatching orders supported by the mobile services (Equations (16), (17), (18)):

Revenue Rate from Retailers = Revenue Rate from Retailers Receiving + Revenue Rate from Retailers Dispatching (16)

*Revenue Rate from Retailers Receiving = Total Farm Orders Shipment Rate*Receiving Unit Fee* (17)

*Revenue Rate from Retailers Dispatching = Total Retailer Orders Shipment Rate * Dispatching Unit Fee* (18)

In a similar way, "Revenue Rate from Farm Dispatching" measures the revenue from farms using the mobile application and its optional features to deliver orders to retailers (Equation (19):

*Revenue Rate from Farm Dispatching = Total Farm Orders Shipment Rate*Dispatching Unit Fee* (19)

The weekly revenue from new adopters of the base application is computed as per Equation (20):

App Adoption Revenue = WebApp Unit Price[(Consumers-Consumers (T−1)) + (Retailers-Retailers (T−1)) + (Farms-Farms (T−1))]* (20)

Finally the variable "Total Cumulated Revenue" is calculated by summing the weekly revenue (Equations (21) and (22)):

Total Revenue per Week = App Adoption Revenue + Orders Fees Revenue (21)

Total Cumulated Revenue = INTEG (Total Revenue per Week, 0) (22)

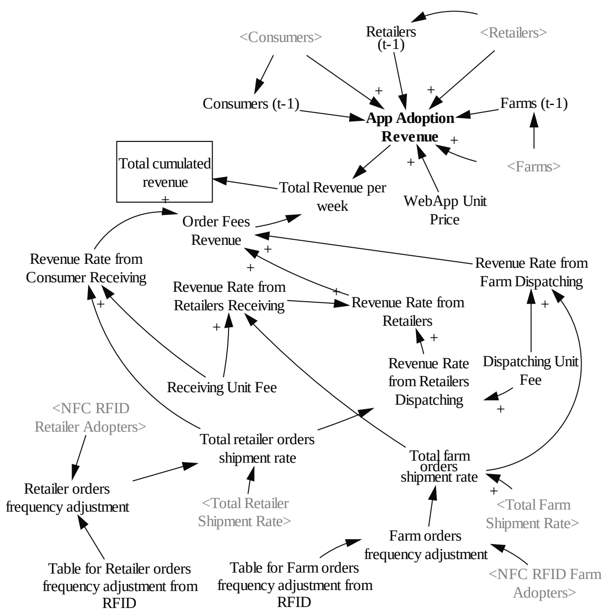

Fig.11 Revenue

B. Analysis of Results

The SD model was calibrated by using numerical data coming from the interviews with the SC partners and past data and information provided by the service provider company. The model was then simulated over the predefined time horizon. Both the adoption of the base application and the adoption of the additional features have been analyzed.

A first result is that the availability of the optional services has a positive influence on the diffusion of the base application because it shortens its market saturation time. When no optional features are available, all the farms, retailers, and consumers in the reference SC adopt the application in respectively 82.4 weeks, 9.4 weeks, and 12.6 weeks. When the optional services are available, they adopt the base application in 79.6 weeks, 8.8 weeks, and 11.6 weeks respectively. The reduced improvement in the adoption period is due to an already quick diffusion of the base application because of its characteristics that are innovative in the analyzed SC.

Another interesting outcome is that the diffusion processes of the optional features are very similar to the diffusion process of the base mobile application, for all the three SC echelons. As an example, Fig.12 compares the evolution overtime of the consumers adopting the base application (first line from the left) with the growth in the number of consumers also adopting the payment management feature (second line from the left). This witnesses the great appeal the three offered options have on the potential users.

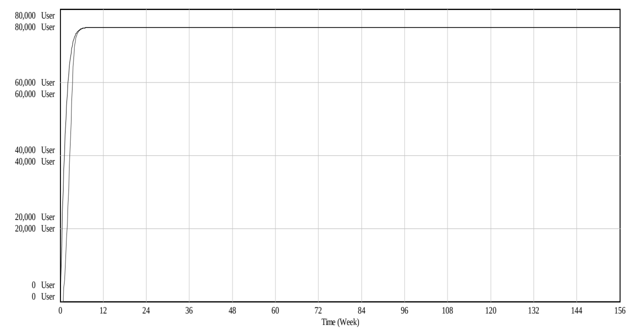

Fig.12 Diffusions among Consumers

Additionally, simulations show how the diffusion of the optional services drives the diffusion of the base application. Taking again the case of consumers, Fig.13 represents the dynamics of the diffusion of the base application under different adoption rates of the three additional features. In particular, the diagram contrasts the diffusion when no additional services are offered (second line from the top) and when they are available and characterized by a normal adoption rate (first line from the top), a low adoption rate (third line from the top), and a very low adoption rate (fourth line from the top). As it can be seen, the slower the adoption process of the optional features, the slower the diffusion of the mobile application.

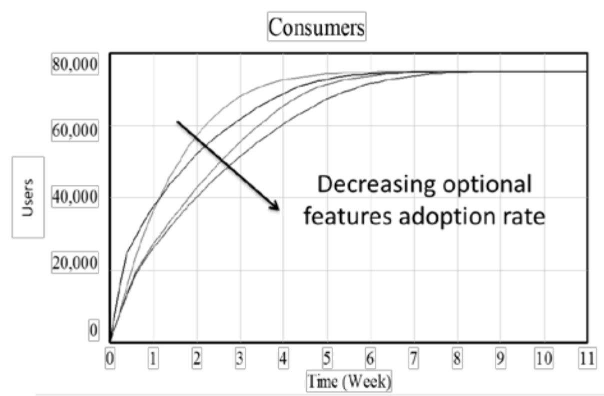

Fig.13 Consumer Diffusion of Base Application

The diffusion of the optional features among users, and in particular the one associated with product traceability management, has also a positive impact on the inventory management and ultimately on the revenue from the application services for the service provider company. As a matter of fact, the increased availability of real time information allows operating with a lower inventory level. Since the demand for the kind of products at issue can be considered steady, this means that SC players will issue orders more frequently. Such increase in the order frequency implies more online information exchanges by means of the mobile application and thus more revenue for the company providing the service. In fact, as mentioned in Section 3, a fee is charged for each dispatching and receiving transaction managed by the mobile application. In order to quantitatively understand the effect of reduced inventory levels on the service provider's revenue, a scenario analysis was carried out. In Fig.14 the situation when no additional services are available (fourth line from the top) is compared with the situation when they can be adopted. Three scenarios were considered: 10% (third line from the top), 30% (second line from the top), and 50% (first line from the top) increases in the order frequency. As it can be seen, the increase in the revenue is quite significant.

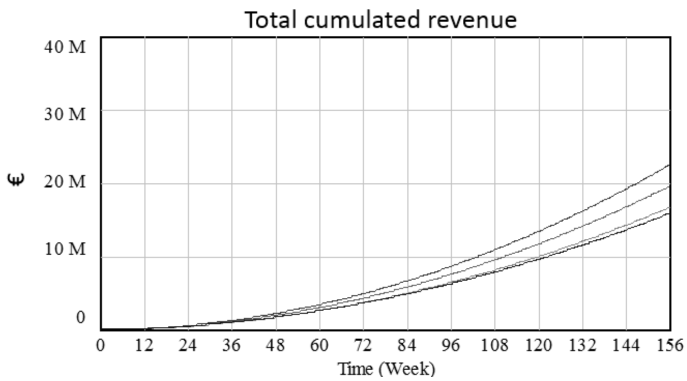

Fig.14 Service Provider's Revenue

Sensitivity analysis of the model was also performed and its results gave interesting insights for policy making.

First of all, the authors studied how the diffusion of the mobile application changes when the model parameters associated with the efficiency and reliability of its services simultaneously change. The outcomes demonstrate how these characteristics affect the adoption by farms and consumers, while the adoption by retailers is not influenced by efficiency and reliability. The diagrams in Fig. 15 present the confidence bounds within which the values of the output variables ("Consumers", "Retailers", and "Farms") can be found with a probability of 50%, 75%, 95%, and 100% as the model parameters associated with the efficiency and the reliability of the mobile services randomly vary out of a triangular distribution between 0 and 1. As it can be seen from the figure, the width of the confidence bounds related to the variables "Farms" and "Consumers" are very limited and close to the base case line but they still prove a certain degree of variability of such variables as the efficiency and the reliability of the service change. On the contrary, the diffusion curve of the retailers does not change with small variations in the efficiency and the reliability values. The retailers still find beneficial to their business to adopt the application even with slightly decreased information exchange efficiency and reliability. This is because the local fresh food industry is characterized by so little coordination and information integration among SC partners that the advantages of using a tool able to concentrate different pieces of real time information can overcome the disadvantages due to small deficiencies in its service level. Such reason also explains the limited sensibility of consumers and farms to small variations in efficiency and reliability.

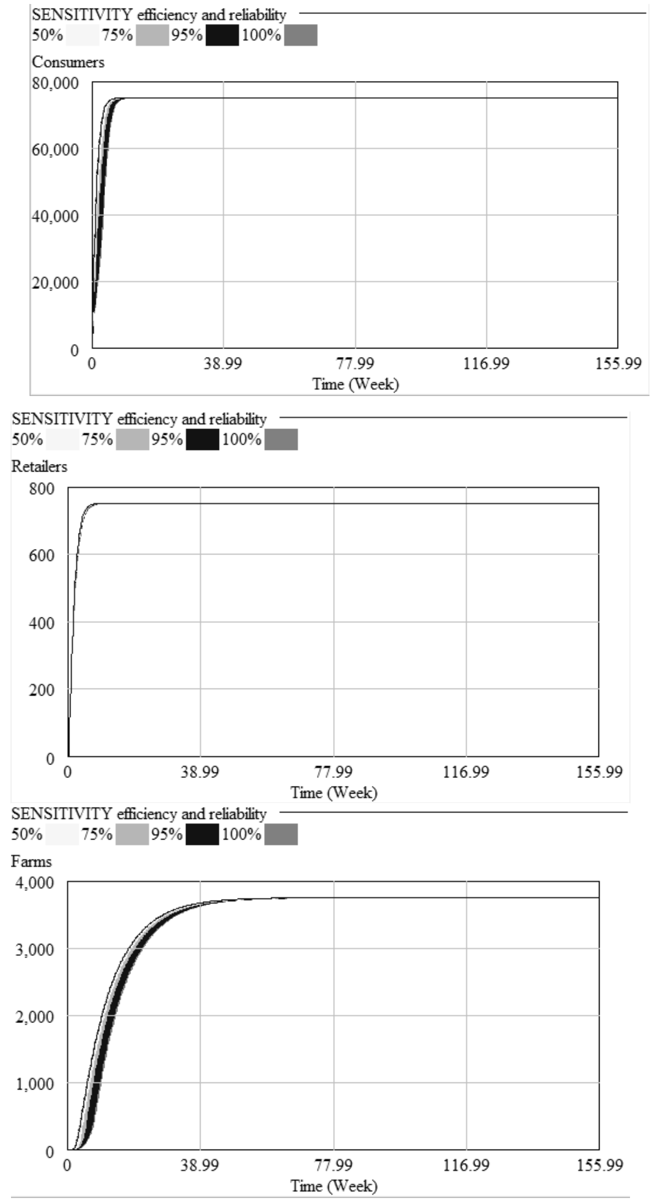

Fig.15 Sensitivity analysis: service efficiency and reliability

As far as pricing is concerned, the sensitivity analysis revealed that farms, retailers, and consumers do not base their adoption decisions either on the price of the mobile application or on the unit fees for receiving and dispatching services. Changes in these values do not significantly affect diffusion as displayed in Fig.16 and Fig.17 for the case of consumers. Similar trends were obtained for farms and retailers. In particular, Fig. 16 shows how the number of consumers adopting the mobile application varies with simultaneous changes in "Receiving Unit Fee", "Dispatching Unit Fee", and "WebApp Unit Price". Fig. 17 analyses random changes in just the variables "Receiving Unit Fee" and "Dispatching Unit Fee". The confidence bounds are all overlapped with the base case line.

Therefore, users are willing to pay even a slightly high price in order to get services supporting SC coordination and information integration.

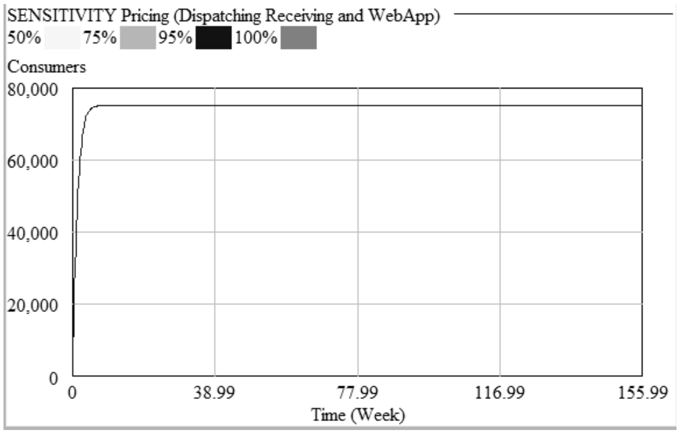

Fig.16 Sensitivity analysis: WebApp price, receiving and dispatching fees

Fig.17 Sensitivity analysis: receiving and dispatching fees

V. Policy Making

The analysis of the outcomes of the SD model suggested some key policies in order to stimulate the diffusion of the mobile application and the associated optional features.

First, given the importance of the adoption of the additional services to both the diffusion of the mobile application and the service provider's revenue, it is highly recommended conducing campaigns to make all the SC echelons aware about the advantages of implementing product traceability systems, electronic payment systems, and "time sensitive" deliveries. The benefits of managing them through the mobile application should be clear to the potential users. Therefore, the service provider's advertising action should be focused on such topics.

Second, the efficiency and reliability of the mobile application designed for placing and managing orders and for tracking and assisting routing of deliveries prove to be determinant aspects to catalyze and speed up its adoption. Thus, a considerable level of efficiency and reliability of the offered services should be ensured in order to stimulate its diffusion, especially among farms and consumers. In fact, they are the players whose adoption is more affected by changes in these characteristics. To this end, the service provider should for example increase the reliability of data transmission through the 3G and 4G networks. Adopting farms would activate persuasion upon retailers and, at the same time, satisfied consumers would facilitate adoption from "word of mouth" by additional retailers. In a similar way, the retailers will in turn act to increase the communities of adopter farms and consumers and also make their own adopter community growth.

Finally, the pricing policy results not to be determinant in addressing the dynamics of adoption by the SC players because the cost of the application is perceived to be rather inexpensive for the kind of service that is offered and to provide a large potential for economic return from accrued business growth. As a consequence, the service provider company can adjust its pricing policy according to the expected dynamics of revenue growth.

VI. Discussion

An appropriate information and logistics structure governing the SC activities is of paramount importance for the local fresh food industry, which is characterized by market segmentation and little coordination among suppliers and customers [8]. Additionally, increasing the quantity of information about the products and the different transactions involving them satisfies the final consumers' need to know the origin and the "history" of what they buy. Mobile communication technologies can help to meet these goals because of their large diffusion and the possibility of managing information real time.

The present work builds on the lack of contributions developing ex-ante feasibility studies about technological innovations in the local fresh food SCs involving all the echelons. A reference methodology to study the impacts of new SC solutions on the key stakeholders and to formulate business policies is proposed. In particular, a SD model to evaluate the diffusion of a mobile application supporting the management of SC operations as well as real time information integration and exchange is developed.

Being comprehensive in nature, the present approach enables to capture all the different dimensions of the problem. Additionally, by integrating the Bass diffusion model with the SC model, it allows to study the innovation adoption not only from a commercial perspective but also from an operational one, by investigating its effects on SCM activities. Finally, the flexibility of the SD methodology enables not only quantitative but also qualitative evaluations according to the availability of information.

The developed SD model has both a theoretical and a practical value. From an academic point of view it stimulates the combination and adaptation in the area of SCM of literature-based SD models addressing the topic of innovation diffusion. From a practitioners' point of view, the proposed approach offers a roadmap to identify the key enabling factors of the diffusion of mobile technology in the fresh food sector and to simulate their impact overtime. This can purposefully complement feasibility studies and marketing investigations when either introducing new services or upgrading existing ones. Also, it may support decision making about specific business policies.

Of course, some limitations can be recognized in this work. First of all, in the attempt to be as much comprehensive as possible, the SD model is quite large and so, in order not to excessively complicate it, a number of simplifications were introduced. For instance, some variables such as those related to satisfaction and inventory levels are sort of average values that takes into account both the users adopting the base application and the users adopting the additional features. Second, just one reference SC in the fresh food sector has been analyzed, although involving a significant number of players. Further investigations on different SCs are needed in order to generalize the results. Third, the approach requires a strong interaction with potential users, which might not be possible in some situations depending on the degree of stakeholders' commitment. Finally, the present research has just focused on the economic impact the diffusion of the mobile application has on the company providing the service, without analyzing the effects on the profit margins of retailers and farms.

Future research efforts will be directed towards applying and adapting the SD model to other SCs in the fresh food sector in order to validate the approach. Moreover, underlying simplifying assumptions will be removed by developing separate SD models if required. Finally, it would be interesting to investigate how the advantages brought by using the application can affect the profit margins of retailers and farms.

VII. Conclusion

The work develops a SD model to study the diffusion pattern as well as the SC impacts of a new mobile application supporting SCM operations in the fresh food industry. The possibility of integrating optional features in the application has been explored. Business policies to stimulate the adoption have been derived from simulation outcomes. The model will be applied to different SCs in order to validate the approach and extended to include the implications of the use of the application on the profit margin of each SC partner.

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