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Digitally enabled food sharing platforms towards effective waste management in a circular economy: A system dynamics simulation model

Meisam Ranjbari [a,*], Zahra Shams Esfandabadi [b,c], Peer-Olaf Siebers [d], Paola Pisano [a], Francesco Quatraro [a,e]

[a] Department of Economics and Statistics "Cognetti de Martiis", University of Turin, Turin, Italy
[b] Department of Industrial Engineering and Innovation Sciences, Eindhoven University of Technology, Eindhoven, the Netherlands
[c] Department of Management, University of Turin, Turin, Italy
[d] School of Computer Science, University of Nottingham, Nottingham, UK
[e] Collegio Carlo Alberto, Turin, Italy

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ABSTRACT

As a solution to tackle the food waste (FW) challenge, digitally enabled food sharing platforms (FSPs) are emerging as FW warriors and anti-waste social movements. Despite the rapidly growing number of users, the amount of FW prevented per user in these platforms is relatively low. Hence, the real contribution of FSPs to the circular economy (CE) by preventing FW is still blurred. To fill this gap, a System Dynamics simulation model is developed in this research to unfold how people adopt such platforms over time, and how such platforms contribute to the CE through FW prevention. The model is used to simulate the adoption and performance of Italy's Too Good To Go (TGTG) platform spanning 2015-2060 as a reference case. The results show that although TGTG is a successful FSP in terms of adoption, it can still significantly improve in terms of performance. Besides, while the current TGTG's marketing strategy is effective, knowledge-enhancing activities should be strengthened to improve performance. Hence, this research recommends a winning policy, which can reduce approximately 3% of the total FW generated at the country level (Italy) in 2060, a significant contribution to the CE transition.

1. Introduction

Effective waste management practices, spanning from waste prevention as a priority in the waste hierarchy to proper disposal, play a significant role in the regenerative nature of the circular economy (CE) that aims to close supply chain loops (Lotfian Delouyi et al., 2023; Ranjbari et al., 2021a). While food loss mainly takes place at the production, postharvest, and processing phases of the food supply chain, food waste (FW) mostly occurs at the later stages of the chain, highlighting the need to consider habits, behaviors, and consumption patterns of consumers and retailers (Morone et al., 2018). In this vein, while in developing countries, FW is mainly generated at the early stages of the food supply chain (i.e., food loss) due to technical and financial constraints, in developed countries, it largely arises at the later stages of the chain due to consumer behavior (Falcone and Imbert, 2017). Hence, incorporating FW prevention and reduction plans and incentives at the consumption level into national policy agendas seems crucial in effective waste management in transitioning towards a CE.

Digitally enabled food sharing platforms (FSPs) have emerged to prevent FW and to save the environment in a CE paradigm. FSPs enable local communities to address both FW concerns and food accessibility, as an effective action towards achieving Sustainable Development Goals 2 (zero hunger) and 12 (responsible consumption and production) introduced by the United Nations (Lucas et al., 2021). In this regard, FSPs face several challenges, such as the impact assessment of food sharing on sustainability and the CE (Mackenzie and Davies, 2019; Michelini et al., 2020), the rebound effects of such platforms for production and consumption (Meshulam et al., 2022; Yu et al., 2022), and the adoption of FSPs in urban communities (D'Ambrosi, 2018). However, given the novelty of the urban FSPs, the contribution of such initiatives to the CE transition in the food supply chain is still blurred (Sarti et al., 2017) and lacks sufficient empirical research.

On the one hand, the number of users of FSPs such as Too Good To Go (TGTG) is notably increasing. For instance, TGTG's user count in Italy has experienced a rapid surge, surpassing 6.9 million users by the end of 2022 within less than four years (TGTG, 2022a). The main reasons

* Corresponding author.
E-mail address: meisam.ranjbari@unito.it (M. Ranjbari).

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behind such a rapidly increasing adoption rate might be (i) the willingness of people to prevent FW and help the environment through using such platforms, whose providers claim they are anti-waste warriors, and (ii) the economic attractiveness for some parts of the community, especially the vulnerable population who care about discounted prices offered by the points of sale through the TGTG app. However, the level of diffusion of using such platforms among communities in the future is not clear.

On the other hand, in contrast with the increasing number of users, the average number of saved food bags per user per year is quite low. For instance, in Italy, from March 2019 to the end of 2022, only 10 million food bags (i.e., magic boxes) have been saved by 6.9 million TGTG users (TGTG, 2022a), which accounts for approximately less than 0.4 of a food bag per user per year. Hence, the paradox of a highly increasing number of users with low effective usage of TGTG in terms of the number of food bags saved per user per year calls for further investigations. In other words, the contribution of FSPs to FW prevention and creating a circular food system is not clear and faces some challenges. While such platforms are frequently considered as a promising strategy to reduce FW (Makov et al., 2023), others argue that they can lead to a rebound effect and provide some extra lines of production and consumption (Meshulam et al., 2022; Yu et al., 2022). Hence, the potential of FSPs to prevent FW and support the circular food system over time is still blurred.

Therefore, the research presented in this paper aims to develop a computational model to simulate the diffusion of digitally enabled FSPs over time and predict their impact on FW prevention and the CE transition. To this end, a System Dynamics (SD) model is developed, and the simulation results for the TGTG platform in Italy, as a reference case, are presented. To the best of the authors' knowledge, this is the first diffusion model developed for FSPs, which significantly contributes to the research and developments in this emerging area of research in the food sector towards a CE. Using the developed simulation model, this article tries to answer the following research questions (RQs):

- RQ1. How will the diffusion of digitally enabled FSPs evolve in the future?
- RQ2. To what extent can digitally enabled FSPs help FW prevention in a CE?

The motivation behind this research is to address the need for understanding the diffusion and impact of digitally enabled FSPs on FW prevention and transitioning towards a CE. The research seeks to fill a significant gap in the existing literature by developing a simulation model to provide valuable insights and contribute to the emerging field of research within the food sector towards achieving a CE. Hence, the provided insights contribute to the existing literature in several ways. Firstly, it aims to simulate the diffusion of digitally enabled FSPs over time, providing valuable insights into their potential growth and adoption patterns. These insights have direct applicability in real-world scenarios, particularly for businesses operating in the food sector seeking to transition toward a CE with a focus on FW prevention. The result is groundbreaking in the FSPs domain, as it constructs an SD simulation model, calibrated for the TGTG platform in Italy, marking the first attempt of its kind. To the best of the authors' knowledge, no prior diffusion model for FSPs has been created. Secondly, this research addresses two important questions that are crucial for the advancement of the food sector towards the CE transition. The first question (RQ1) focuses on predicting the future evolution of digitally enabled FSPs, shedding light on their potential reach and impact in the coming years. By exploring this aspect, the study provides valuable insights into the growth trajectory of FSPs, enabling policymakers and industry stakeholders to make well-informed decisions. The second question (RQ2) delves into the role of digitally enabled FSPs in addressing FW prevention within a CE framework. By investigating the extent to which these platforms can contribute to FW prevention, the research offers practical implications for reducing FW and advancing the principles of the CE.

The remainder of this paper is organized as follows. Section 2 provides an overview of the food sharing concept, including its business models. Additionally, it highlights the unexplored research landscape within this domain, identifying key areas that have yet to be thoroughly investigated. Section 3 describes the adopted methodology, outlining different steps in SD modeling and the types of data used in such simulation models. Section 4 introduces the main structure of the model and provides details on building its sub-systems to do the simulation. Within Section 5, the TGTG platform in Italy, as a reference case to illustrate the model performance, is introduced, and the relevant data to parameterize the model is presented. Simulation results for different scenarios regarding Italy's TGTG within the period 2015-2060 are presented and analyzed in Section 6. Then, based on the insights gained in this research, the potential directions for future research are discussed in Section 7. Finally, Section 8 concludes the paper by summarizing the findings from the conducted research.

2. Food sharing platforms: an overview and unexplored research landscape

The advent of online networks and digital platforms has notably changed distribution and redistribution channels, leading to advancing sharing economy platforms to connect the demand and supply sides of economic systems (Ranjbari et al., 2018). In this regard, sharing durable products, such as bikes, cars, rooms and houses, instruments, etc., has gained momentum either in peer-to-peer or business-to-consumer business models. With this premise in mind, there has been a growing focus on the exploration of digital platforms for alternative distribution channels in food supply chains as a potential solution to tackle the FW challenge worldwide. However, using redistribution channels in the food sector is more challenging than for other products since food is a particular type of product due to several facts, such as (i) food is a life necessity, (ii) food is a human right, (iii) food is highly sensitive in terms of health, safety, durability, storage life, and quality, and (iv) food has a specific social and cultural value (Zurek, 2016). Therefore, incorporating sharing economy principles in the food sector through digitally enabled platforms faces several barriers, including (i) trust among stakeholders, (ii) behavior and consumption patterns of different players within the food supply chain, and (iii) satisfying multiple needs for heterogeneous actors (de Almeida Oroski and da Silva, 2022).

There is no globally agreed definition for the concept of "food sharing" (Davies and Legg, 2018). Referring to the sharing economy definition, as an economic system utilizing online platforms to facilitate giving temporary access (i.e., without ownership transformation) to idle resources (Ranjbari et al., 2018), food sharing might be defined as selling food surplus through online platforms or gifting foods to food banks, as well as peer-to-peer marketplaces that facilitate the sharing activities (Davies and Legg, 2018). Although food sharing activities were initially limited to household or kinship relationships, such as family or friends, the emergence of digital platforms has extended the domain of food sharing beyond this, so that such activities can mobilize food sectors to share food surpluses with the needy (Octavia et al., 2022).

Furthermore, since this phenomenon is still new, there is no common understanding of the business model of such platforms and how they work and create value within the food supply chain for the involved stakeholders. Such platforms not only provide opportunities for peer-to-peer exchanges of food but also facilitate the transfer of unsold food from businesses (such as restaurants, supermarkets, bars, cafés, etc.) to consumers to reduce FW (Lucas et al., 2021). Such transfers within FSPs could be either non-monetary (e.g., the OLIO app) or monetary based on a discount pricing strategy (e.g., the TGTG app). Conducting a hierarchical cluster analysis on 52 food sharing cases, Michelini et al. (2018) categorized food sharing business models into three groups, including (i) the "sharing for money" business model, referring to a business-to-consumer for-profit business model to reduce FW and generate revenues simultaneously, (ii) the "sharing for charity" business model, in which food is collected and distributed to non-profit organizations, and (iii) the "sharing for the community" business model, addressing peer-to-peer business models where consumers share food among each other. Arguably, digitalization in business models has brought some opportunities for existing social supermarkets and food banks to integrate online and traditional channels in distributing food by using web-based platforms and mobile applications (Michelini et al., 2018).

The empirical research carried out to date on technology-assisted food sharing practices are varied in nature, yet all consistently highlight the significant growth in the number of users within peer-to-peer sharing systems (Harvey et al., 2020). However, when examining various food sharing business models, the predominant focus has been on food sharing for charitable purposes, rather than exploring the realms of food sharing for monetary gain or the benefit of the community. Concerning this aspect, OLIO, a prominent FSP, operating in over 120 countries worldwide, has gained recognition for its efforts. Notably, despite being a for-profit entity, OLIO facilitates the exchange of food without any cost or charge to users. OLIO's success lies in (i) effectively addressing FW, (ii) mitigating the environmental consequences associated with surplus food, (iii) community building, (iv) enabling users to save money, and (v) enhancing well-being by providing access to foods (Makov et al., 2023). Nica-Avram et al. (2021) in a study on OLIO to identify the relationship between food insecurity and food sharing networks, showed that food sharing organizations have inherent limitations in their ability to provide extensive assistance or relief to individuals experiencing acute food insecurity. In their study on the drivers of success for OLIO, Mazzucchelli et al. (2021) highlighted the essential and interrelated roles of perception of environmental and social responsibility, consumer familiarity, and community social support in bolstering consumer behavioral response to FSPs.

As previously stated, food sharing business models centered around exchanging food for money have not received significant attention. The current understanding of their adoption, consumer behavior, and the broader impact on the environment, society, and economy is still at an early stage of development. In this category of FSPs, TGTG, as an anti-waste platform, appears to possess a mutually beneficial business model for all participants, since (i) consumers can buy food products at a discounted price, (ii) retailers can sell their unsold food products to cover their cost and generate some lines of revenue, (iii) the TGTG platform gains money through linking buyers to sellers, and (iv) the FW prevented helps the environment, FW management systems, and resource efficiency towards an effective CE transition. Pisoni et al. (2022) in a survey conducted on FSPs and consumer behavior, indicated that (i) younger individuals exhibit a greater openness towards this emerging digital shopping trend, whereas older individuals tend to prefer more conventional methods of purchasing and other off-line alternatives, and (ii) users often opt for using FSPs primarily due to economic considerations rather than environmental motivations. In a similar study, Yamabe-Ledoux et al. (2023) outlined convenience orientation and price consciousness as the primary motivations for using FSPs. However, their research also identified significant barriers to FSPs adoption, including concerns about the safety of redistributed food and hesitance to engage in a sharing community.

Mathisen and Johansen (2022) conducted a pilot intervention study on a group of students to evaluate the effect of using mobile applications designed for FW reduction, considering TGTG as a case. In their research, having observed the changes after a two-month trial use of TGTG, they concluded that although consumers' FW awareness increased, TGTG did not result in any measurable effects regarding FW, improved healthy eating, and personal costs. This might be acknowledged by the fact that changing the everyday food-related habits and behaviors of consumers is not easy (Boulet et al., 2021) and requires sufficient investment and effective initiatives in the long term. According to the research conducted by Fragapane and Mortara (2022), TGTG users in Italy seem to put more emphasis on the quality of food and saving money than on FW prevention. Vo-Thanh et al. (2021) through conducting a semi-structured interview with consumers and retailers involved in TGTG in France, highlighted that the main success factors of TGTG in accomplishing its social mission are social, emotional, and functional values.

Zaman et al. (2021) identified TGTG as a valuable food distribution channel during crises like the COVID-19 pandemic. They found that customers often make additional purchases when collecting their TGTG food orders, presenting a cross-selling potential for retailers to boost their earnings. Moreover, among those who discover a shop through TGTG, 76% convert into customers, while 58% of TGTG users become regular customers. (TGTG, 2022b). In contrast, although TGTG has provided an opportunity to prevent FW through distributing food surplus, it can result in rebound effects, leading to emerging different lines of businesses for retailers to sell more food products. In this regard, as highlighted by Yu et al. (2022) and Meshulam et al. (2022), further research is required to investigate the potential rebound effects of FSPs to see whether the food sold on the platform is effectively a surplus or a planned production to generate revenue.

However, despite the evident advantages of FSPs like TGTG, the existing academic research in this specific area remains significantly limited. Hence, given the novelty of the topic, attention and further investigation are crucial to address the existing research gap. Future studies should delve into the dynamics, challenges, and impacts of such platforms, shedding light on their potential for fostering the CE transition in sustainable food systems and exploring their long-term implications for various stakeholders involved. By addressing this research gap, we can gain a deeper understanding of the opportunities and barriers associated with these emerging anti-waste platforms, paving the way for informed decision-making and policy development in the context of the CE.

While there has been an observed growth in the number of TGTG users engaging in food sharing services, the extent to which this platform will continue to expand in the future remains uncertain. Additionally, there are certain challenges and uncertainties regarding the actual impact of TGTG in preventing FW. As a result, the full potential of FSPs in promoting FW reduction and facilitating a circular food system is yet to be fully understood. Hence, the present research aims to simulate the diffusion of FSPs with "sharing for money" business models over time and predict their impact on FW prevention and the CE transition by developing an SD model. The SD simulation tool aids policymakers in addressing the growing complexity of the shift towards a CE by implementing closed-loop thinking and uncovering the causal structures within the system (Guzzo et al., 2022).

3. Methodology

SD is a computer-aided simulation method where a model of causalities in a real-world complex system is developed, parameterized, and validated using real-world information for policy analysis and design (Dianati et al., 2021). This system analysis approach can deal with large-scale, linear, and non-linear interactions, dynamics, and complex systems (Sukholthaman and Sharp, 2016). SD draws upon both quantitative and qualitative methods to involve stakeholders in defining mental models and support scholars to adopt non-linear thinking to understand and map the feedback processes of problem dynamics (Galli et al., 2019; Turner et al., 2016). This mathematical modeling technique is based on ordinary differential equations, is deterministic, and uses a graphical user interface (stock and flow diagrams). Compared to other simulation methods, SD offers a decision framework that extends over the long term and possesses the ability to handle time delays and internal feedback loops that impact the behavior of the entire system (Sterman, 2000). Due to the ability of SD to model complexity and generate simulated scenarios depending on the variations of variables, it has been widely used by scholars in different lines of waste management practices to simulate dynamics and interrelationships in FW management (Lee et al., 2019), biodegradable waste management (Babalola, 2019), municipal solid waste management and financial analysis (Pinha and Sagawa, 2020; Rafew and Rafizul, 2021), and FW reduction and food poverty alleviation (Galli et al., 2019).

Modeling is a creative endeavor where modelers have the flexibility to adopt various approaches and styles. However, following a disciplined process significantly helps modelers develop more reliable models in a reasonable manner. In this regard, Sterman (2000) proposed a five-step process to develop an SD model, including: (1) problem articulation and boundary selection to determine the modeling purpose, (2) dynamic hypothesis formulation to provide a conceptual framework of the complex system, (3) simulation model formulation to convert the conceptual model to a simulation model with equations, (4) model testing to calibrate the model behavior, and (5) policy design and evaluation for improvement to test different scenarios and observe the effects of changes. In this vein, while steps 1 and 2 are often associated with ‘soft systems’ since they need conceptual modeling of the interactions among variables, steps 3 and 4 are associated with the ‘hard systems’ domain since they require quantification (Turner et al., 2016). Having divided modeling into different steps, it should be noted that modeling is not a linear sequence of these steps. Instead, it operates as a feedback process due to the continuous and iterative nature of SD models (Sterman, 2000). The iteration process can occur between any of the five steps involved in modeling.

SD relies on quantitative data to generate feedback models (Luna-Reyes and Andersen, 2003). According to Forrester (1980) and Sterman (2000), three main types of data are required for developing an SD model, including numerical, written, and mental data. Numerical data, such as time series and cross-sectional records, constitute a tiny part of the written data that includes records such as operational procedures, media reports, and any other archival material. On the other hand, mental data, which comprises a substantial amount of information compared to written data, covers all the information only available in people’s mental models, such as their impressions, their understanding of the system, and how the decisions are made. Direct access to mental data is not possible; so, this type of data must be extracted through observations, interviews, or any other possible method.

Although most of our knowledge about the world is descriptive and impressionistic and has never been recorded, such pieces of information play a vital role in understanding and modeling complex systems (Sterman, 2000). Ignoring soft variables and restricting the variables to those for which numerical data are available results in the development of incomplete and wrong models, as “to omit such variables is equivalent to saying they have zero effect – probably the only value that is known to be wrong!” (Forrester, 1961). Therefore, in addition to the numerical data used to build the model, significant attention should be paid to soft variables. If time and cost restrictions allow, Sterman (2000) suggests quantifying soft variables, such as users’ perception of a technology, as it can provide valuable insights into the model. Alternatively, these parameter values can be estimated based on the judgment or ‘educated guesses’ (Homer, 2012). In such cases, the behavior pattern of the model should be checked as the inflection points, equilibrium level, or time to equilibrium deserve more attention than the exact value of the variable at a specific time point (Hekimoğlu and Barlas, 2010). On this basis, the main data that have been used in this research are presented and explained in their corresponding sub-sections of model development.

4. Simulation model development

To gain insight into the dynamics of the diffusion of FSPs in this research, we have considered two innovation diffusion models as foundational frameworks for developing our model. The first model is the diffusion model developed by Struben and Sterman (2008), which is an extension of the basic Bass diffusion model of innovation adoption (Bass, 1969). This model accounts for endogenous word-of-mouth from adopters and includes the effects of marketing and media (Mahajan et al., 2000), substitution among successive technologies (Norton and Bass, 1987), uncertainty about the innovation value (Kalish, 1985), and repurchases (Sterman, 2000). Furthermore, unlike the Bass innovation diffusion model that generates an S-shaped growth curve for technology, this diffusion model incorporates additional diffusion patterns, including rise and demise, stagnation at low penetration levels, and fluctuations. The second model, developed by Shams Esfandabadi (2022), is an extension of Struben and Sterman’s (2008) model for the diffusion of shared platforms within the transportation sector. The development of the current simulation model for FSPs diffusion draws inspiration from both models, weaving together their principles and concepts while incorporating numerous modifications and customizations to accommodate the unique characteristics of perishable food sharing. This adaptation takes into account the specific requirements of FSPs. Therefore, while the present model shares certain similarities with the previously mentioned models, it significantly differs from both.

The current model incorporates concepts from Struben and Sterman (2008) pertaining to customers’ willingness to adopt technology and marketing activities, which are general foundational concepts in technology diffusion. Nevertheless, it diverges from their framework by not accounting for the co-evolution of alternative technologies and infrastructure. This departure is driven by the distinct nature of digitally enabled FSPs, which can experience rapid diffusion without the specific infrastructure requirements typically associated with durable products. Moreover, the current model draws from Shams Esfandabadi’s (2022) structure for educating the young population on product-service systems but differs in two main aspects. Firstly, it extends its scope to encompass knowledge-enhancing activities for both under-aged individuals and adults, enabling the analysis of scenarios aligned with TGTG’s efforts against FW. Secondly, while Shams Esfandabadi’s (2022) model primarily focuses on the impact of knowledge-enhancing activities on technology adoption (e.g., becoming active users), the current model considers the broader influence of these activities, affecting not only technology adoption (i.e., becoming an FSP member) but also user activities (i.e., ordering food bags). Additionally, although both core models address people’s familiarity with technology, we have employed Shams Esfandabadi’s (2022) proposed structure with some modifications due to its relevance to product-service systems. Building upon this foundation, we have developed a significantly modified SD model to simulate the diffusion of FSPs. This model not only allows for the simulation of the app’s diffusion dynamics and app’s performance but also enables assessment of its contribution to the CE and CO_2 emission reduction.

To provide a clear view of the dynamics considered in the developed model, the main feedback loops leading to the key dynamics are illustrated in Fig. 1. The reinforcing loop R1 refers to the social exposure that leads to more adoption of the food sharing app. This loop indicates that higher social exposure, derived from both marketing efforts and effective contacts with app users, leads to heightened familiarity of people with the FSP. This, in turn, enhances the likelihood of individuals considering joining the app. Then, an increase in the number of app users leads to more social exposure, and this positive loop continues. However, the more people are familiar with the FSP, the more they look for information and talk about it with other people (word-of-mouth), leading to a higher familiarity gain, as shown in loop R2. On the other hand, in the absence of sufficient exposure to the app or interactions with app users, individuals gradually lose their familiarity with the platform as it fades from their memory over time, as shown by the balancing loop B1.

Knowledge-enhancing programs can amplify people’s understanding, awareness, and social exposure to digitally enabled FSPs and FW prevention. These programs not only bolster individuals’ familiarity and enhance the attractiveness of joining the app but also motivate them to leverage their app usage and more actively prevent food wastage. Finally, in addition to the amount of FW and CO_2 emission prevented, a CE indicator is considered in the model to estimate the level of

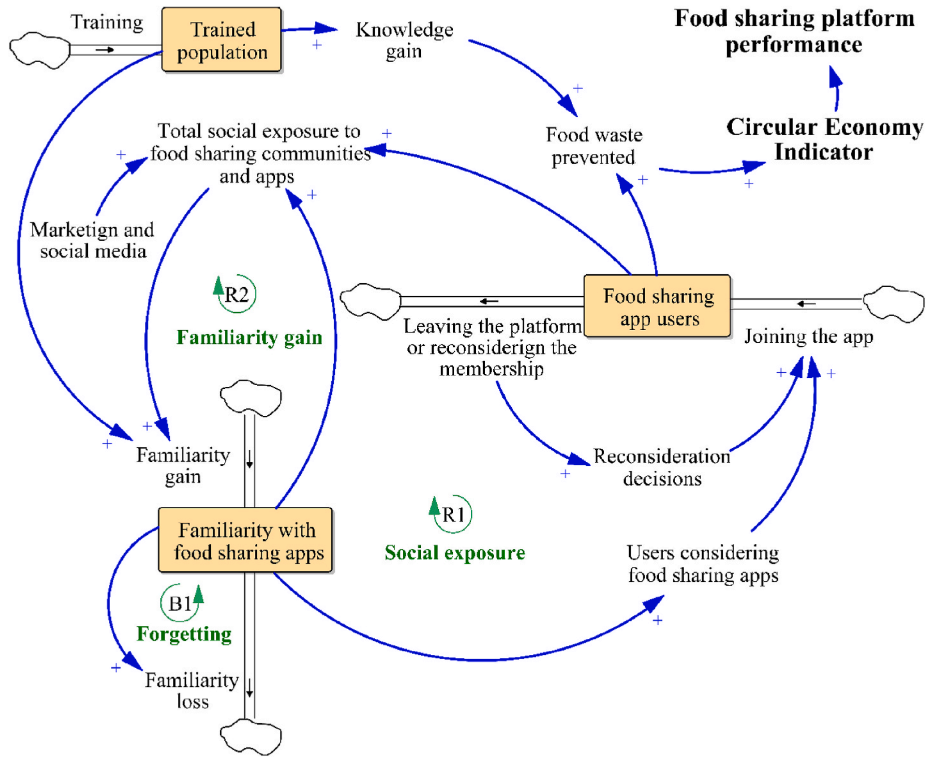

Fig. 1. The conceptual model addressing key feedback loops in the developed model for the TGTG app diffusion.

circularity of the TGTG food sharing app based on the amount of FW prevented.

However, the model is not limited to the loops mentioned. As shown in Fig. 2, the developed model contains several stock and flow structures and auxiliary variables, generating dynamics through numerous loops. The model combines four main elements, including:

(i) the effect of knowledge enhancement programs on the dynamics of the well-informed population regarding FW prevention and CE,
(ii) the accumulation of consumer familiarity from marketing, knowledge-enhancing programs, and word-of-mouth, leading to the adoption of food sharing apps,
(iii) the dynamics linked with the adoption of food sharing apps, and
(iv) the causalities referring to the estimation of FW, CO_2 emission prevented, FSP performance, and the CE indicator.

These elements are presented in sub-sections 4.1 to 4.4, respectively.

4.1. Knowledge enhancement in the population

The research conducted on FSPs with food sharing for money business model reveals that the main motivation behind using these apps is primarily economic considerations rather than environmental motivations (Pisoni et al., 2022). Hence, changing individuals' mindsets concerning environmental issues necessitates extensive endeavors and knowledge-enriching initiatives that require a significant amount of time. In this regard, programs and activities aimed at enhancing knowledge, such as webinars for training, the development of educational materials for schools and colleagues, massive online courses, mentorship programs, and corporate training initiatives, can substantially contribute to raising public awareness and knowledge about the profound consequences of FW on the environment, society, and economy. The effective promotion of science-based environmental activism requires the combined forces of technological innovation and active societal learning (Papachristos and Struben, 2020; Sterman, 2015). Effective diffusion of food sharing apps also requires appropriate societal learning, a huge part of which can happen through knowledge-enhancing programs. The "pact against food waste" initiative launched by TGTG has also taken into account the potential impact of knowledge-enhancing activities on society by highlighting the training webinars for the supermarkets and companies' staff and preparing training materials for schools.

The term "well-informed" population in this research denotes the segment of the population that has received adequate education regarding FW and its effects on various aspects of sustainability, encompassing the environment, society, and economy. On the other hand, the "uninformed" population refers to individuals who are unaware of the profound consequences and implications of the FW crisis, as well as the primary purpose of using FSPs. This purpose involves reducing FW and transitioning towards a CE, rather than being solely driven by factors like lower prices. On this basis, "knowledge-enhancing" programs and plans refer to all educational activities that support the transitioning of the "uninformed" population into the "well-informed" category.

In order to analyze the potential role of training and educating people in the adoption and usage of food sharing apps, a co-flow structure (a parallel stock and flow structure) has been developed to model the dynamics of the population and the dynamics of the well-informed population. As illustrated in Fig. 3, the population flow contains a simple age structure with two age cohorts referring to the under-aged (less than 18 years of age) and adult (18 years of age and older) populations. Similarly, the flow of the well-informed population also includes these two age cohorts, but specifically for the well-informed population. In each of the population stocks in these flows, the assumption of perfect mixing in age groups based on Sterman (2000) is made.

To maintain simplicity and clarity within the model, the birth rate is assumed to be proportional to the total population, and a general death rate based on the overall death rate of the population is considered. Based on the inflows and outflows of the under-aged population and adult population stocks, the population in these two age cohorts can be

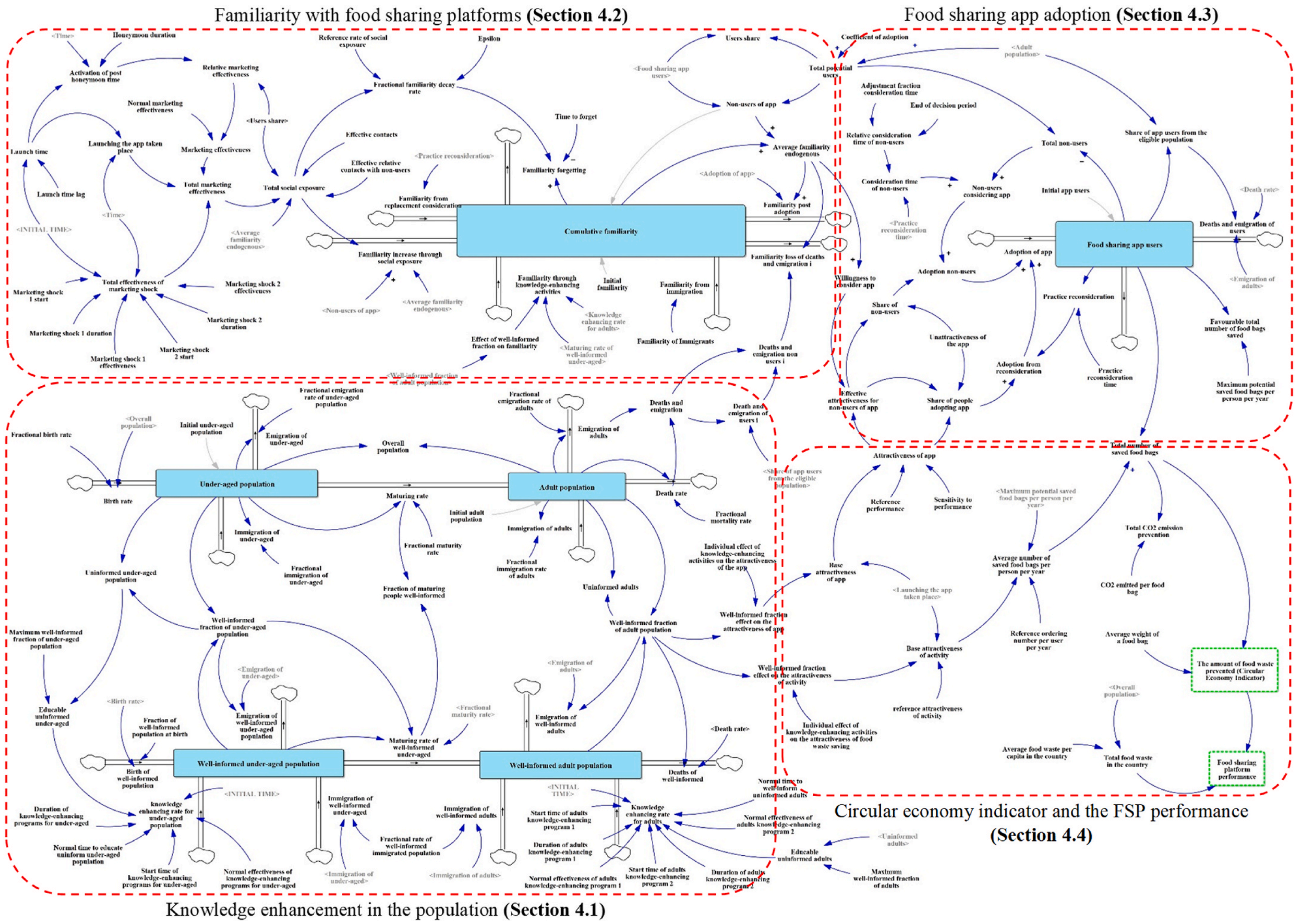

Fig. 2. The key feedback loops in the developed model (this figure is just for illustrative purposes; for details, please refer to Figs. 3-6).

formulated as in Equation (1) and Equation (2), respectively.

$$\mathrm{UPOP(t)}=\int_{t_0}^{t}(\mathrm{BR}+\mathrm{IMUPOP}-\mathrm{EMUPOP}-\mathrm{MR})dt+\mathrm{IUPOP}\ (t_0) \quad \text{Equation 1}$$

$$\mathrm{APOP\ (t)}=\int_{t_0}^{t}(\mathrm{MR}+\mathrm{IMAPOP}-\mathrm{EMAPOP}-\mathrm{DR})dt+\mathrm{IAPOP}\ (t_0) \quad \text{Equation 2}$$

where:

BR: Birth rate.
DR: Death rate.
UPOP: Under-aged population.
APOP: Adult population.
IUPOP: Initial under-aged population.
IAPOP: Initial adult population.
IMUPOP: Immigration of the under-aged population.
IMAPOP: Immigration of the adult population.
EMUPOP: Emigration of the under-aged population.
EMAPOP: Emigration of the adult population.
MR: Maturity rate.

The initial under-aged population and initial adult population refer to the population of these age cohorts at the time t_0 of the simulation. Furthermore, immigration of the under-aged population, immigration of the adult population, emigration of the under-aged population, and emigration of the adult population are proportional to the population in their corresponding age cohorts based on their corresponding fractional immigration and emigration rates. Moreover, maturity rate refers to the growth of under-aged youth and their transition from the under-aged population age segment to the adult population age segment and can be found by multiplying the under-aged population by its corresponding fractional maturity rate, which is the average time required for an individual to leave a younger age cohort and enter the older one (Mielczarek and Zabawa, 2016). Therefore, the fractional maturity rate is assumed to be the inverse of the age cohort's length (Vahidi Monfared and Moini, 2019), which is 18 in the current model. On this basis, the maturing rate is calculated as follows:

$$\mathrm{MR}=\mathrm{UPOP}\times\mathrm{FMR} \quad \text{Equation 3}$$

where:

FMR: Fractional maturity rate $= 1/18$

In parallel with the population flow structure, the well-informed population structure is formulated, which has two inflows for knowledge enhancement among under-aged and adult populations in addition to birth, death, maturing, emigration, and immigration rates. The well-informed under-aged population and well-informed adult population stocks can be formulated as in Equation (4) and Equation (5), respectively.

$$\mathrm{WUPOP(t)}=\int_{t_0}^{t}(\mathrm{BWPOP}+\mathrm{IMWUPOP}+\mathrm{KRUPOP}-\mathrm{EMWUPOP}-\mathrm{MRWU})dt \quad \text{Equation 4}$$

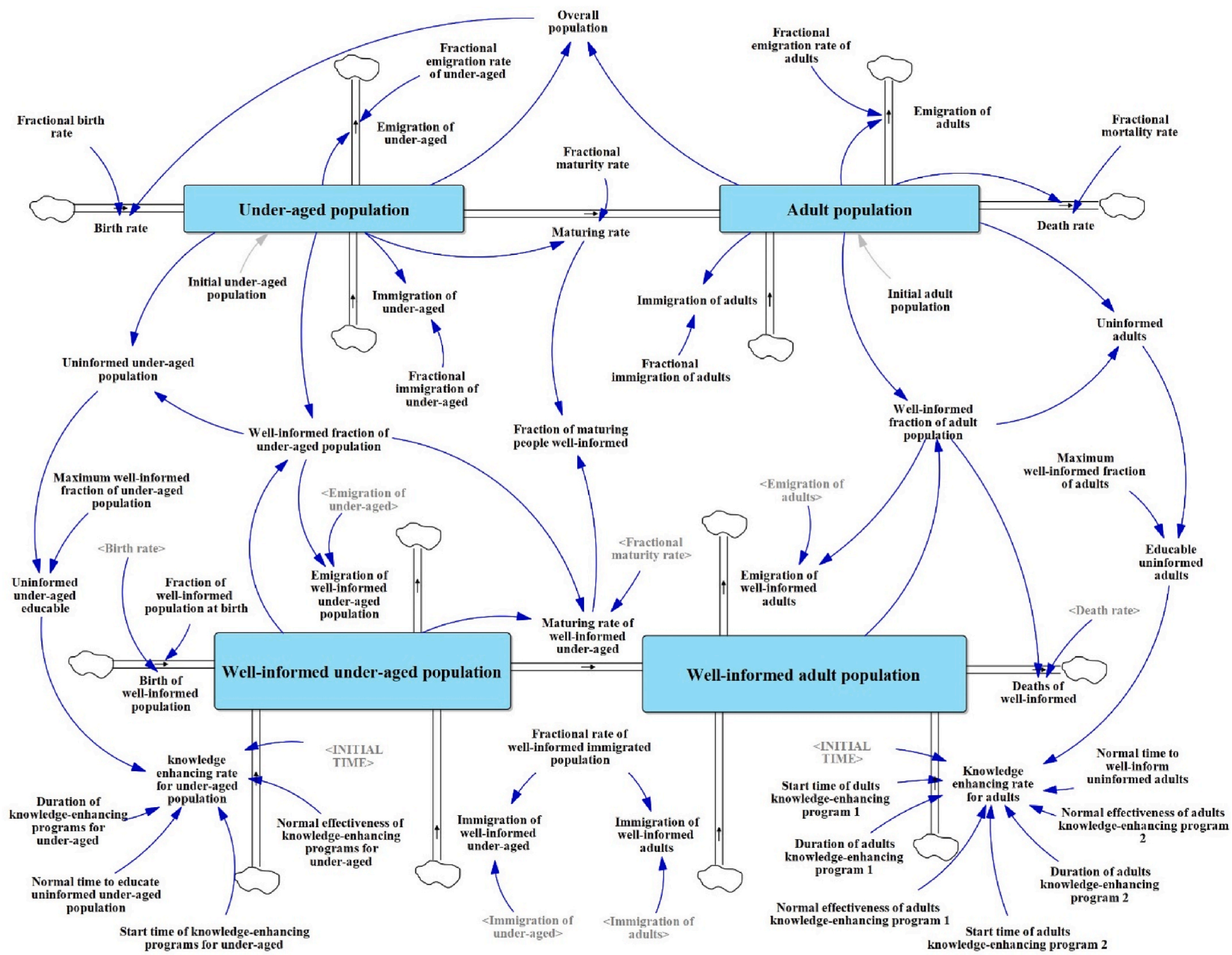

Fig. 3. The co-flow structure addressing knowledge enhancement in the population.

$$\text{WAPOP}(t)=\int_{t_0}^{t}(\text{IMWAPOP}+\text{MRWU}+\text{KRAPOP}-\text{DWPOP}-\text{EMWAPOP})dt \quad \text{Equation 5}$$

where:

WUPOP: Well-informed under-aged population.

WAPOP: Well-informed adult population.

BWPOP: Birth of well-informed population $= 0$

IMWUPOP: Immigration of well-informed under-aged population.

EMWUPOP: Emigration of well-informed under-aged population.

KRUPOP: Knowledge enhancement rate for the under-aged population.

MRWU: Maturing rate of well-informed under-aged population.

IMWAPOP: Immigration of well-informed adult population.

KRAPOP: Knowledge enhancement rate for the adult population.

DWPOP: Deaths of well-informed population.

EMWAPOP: Emigration of the well-informed adult population.

The birth rate of the well-informed population is set to zero since nobody is born trained. However, this rate has been considered in the model to keep the co-flows similar. Emigration of well-informed under-aged and adult populations follow Equation (6) and Equation (7), respectively.

$$\text{EMWUPOP} = \text{WFUPOP} \times \text{EMUPOP} \quad \text{Equation 6}$$

$$\text{EMWAPOP} = \text{WFAPOP} \times \text{EMAPOP} \quad \text{Equation 7}$$

where:

WFUPOP: Well-informed fraction of the under-aged population.

WFAPOP: Well-informed fraction of the adult population.

Knowledge enhancement rates for the under-aged and adult populations are affected by start time, duration, and effectiveness of knowledge-enhancing programs, as well as the normal time to increase the knowledge of the uninformed population, and the educable uninformed portion of the population for each of these age segments. Knowledge-enhancing activities are considered to start at a specific time with specified effectiveness and last for a particular period. Therefore, in order to formulate the equations referring to these rates, the function STEP in the Vensim software has been used. STEP function returns zero until a specific time and after that, jumps to a specified value. Equation (8) and Equation (9) present the formulation of the knowledge enhancement rate for the under-aged population and the knowledge enhancement rate for adults, respectively. According to the TGTG's pact against FW (TGTG, 2021), training for adults has already been started (since 2021); thus, two different sets of variables for knowledge enhancement have been considered for adults to both simulate the effect of the current training activities and test scenarios regarding changes in the knowledge enhancement activities in future. However, depending on the FSPs considered while using this simulation model, the number of

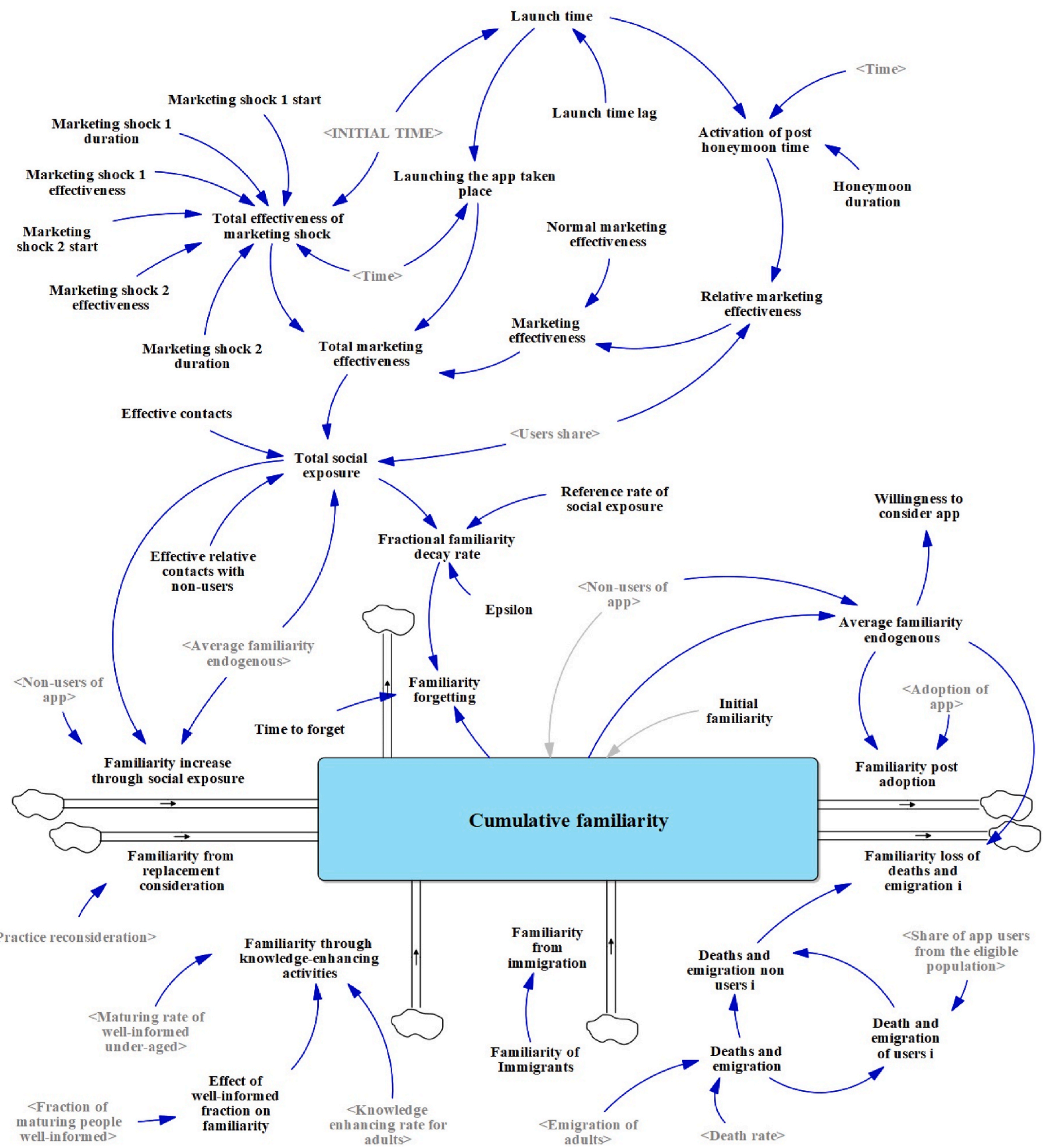

Fig. 4. The Sub-system of familiarity with the FSP.

programs can increase or decrease.

$$\text{KRUPOP} = (\text{STEP}(1, \text{INITIAL TIME} + \text{ESU}) - \text{STEP}(1, \text{INITIAL TIME} + \text{ESU} + \text{EDU})) \times \text{EUU} \times \text{NEKU} / \text{NEUU}$$

Equation 8

$$\text{KRAPOP} = (\text{STEP}(1, \text{INITIAL TIME} + \text{KSA1}) - \text{STEP}(1, \text{INITIAL TIME} + \text{KSA1} + \text{KDA1})) \times \text{EUA} \times \text{NEKA1}/\text{NEUA} + (\text{STEP}(1, \text{INITIAL TIME} + \text{KSA2}) - \text{STEP}(1, \text{INITIAL TIME} + \text{KSA2} + \text{KDA2})) \times \text{EUA} \times \text{NEKA2}/\text{NEUA}$$

Equation 9

where:

ESU: Education start time for under-aged.

EDU: Education duration for under-aged.

NEKU: Normal effectiveness of knowledge-enhancing programs for under-aged.

NEKA: Normal effectiveness of knowledge-enhancing programs for adults.

NEUU: Normal time to educate the uninformed under-aged population.

EUU: Educable uninformed under-aged population.

KSA1: Knowledge-enhancing program #1 start time for adults.

KSA2: Knowledge-enhancing program #2 start time for adults.

KDA1: Knowledge-enhancing program #1 duration for adults.

KDA2: Knowledge-enhancing program #2 duration for adults.

NEKA1: Normal effectiveness of knowledge-enhancing program #1 for adults.

NEKA2: Normal effectiveness of knowledge-enhancing program #2 for adults.

EUA: Educable uninformed adults.

NEUA: Normal time to educate the uninformed adult population.

Although both age cohorts receive training and use knowledge-

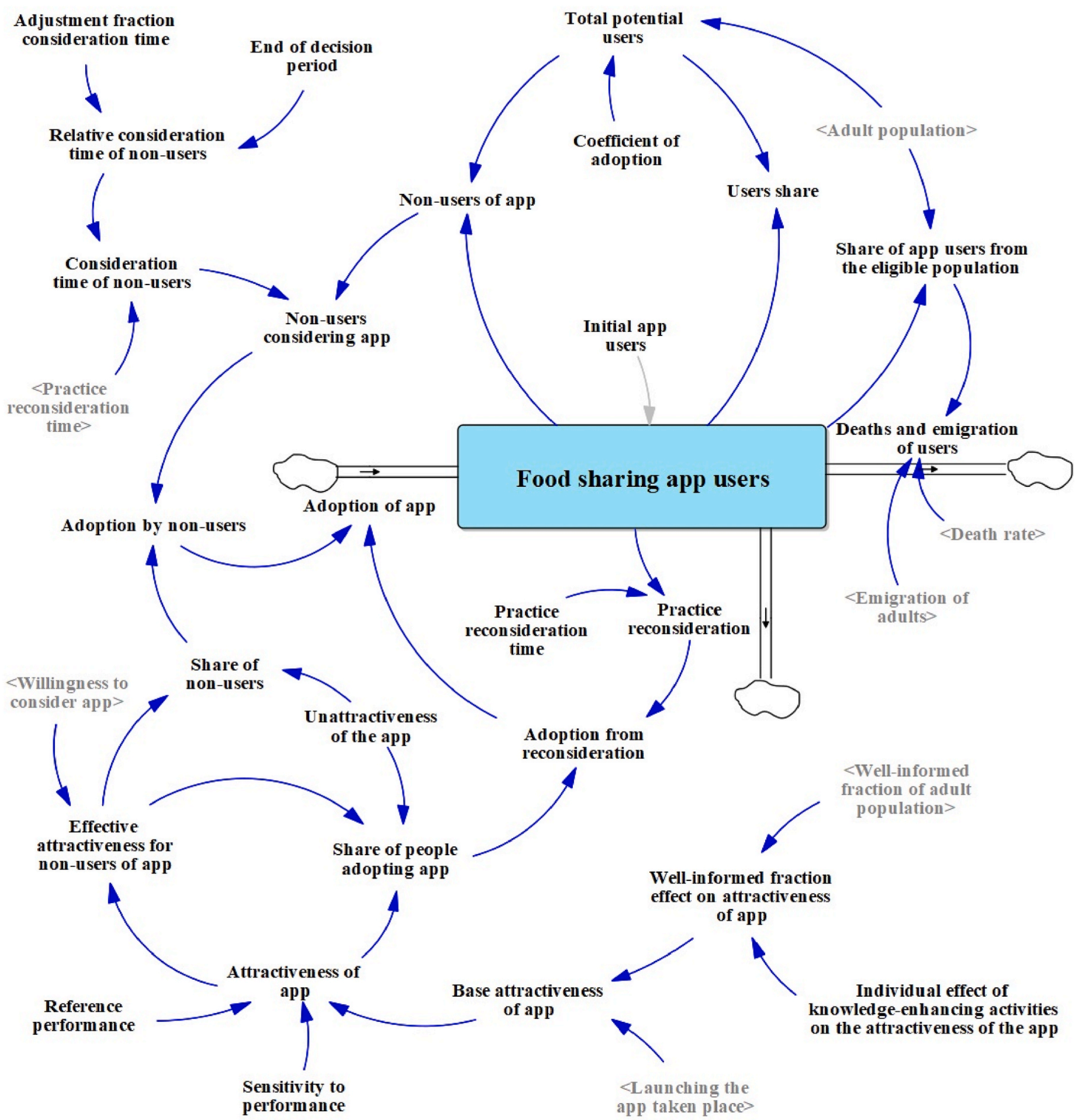

Fig. 5. The sub-system of the food sharing app adoption.

enhancing programs (with different times and effectiveness), only adults are eligible to join and use the FSP. However, when the under-aged population is trained, this knowledge can be transferred to the adult age cohort through the growth and maturity of the under-aged population. The well-informed fraction of the adults is expected to be more willing to join and use the FSP, as the attractiveness of the app and its usage can increase through knowledge enhancement. Similar to the maturity rate in the population flow, the well-informed under-aged maturing rate is linked with a fractional maturity rate, which is the inverse of the age cohort's length and is $^{1}/_{18}$ in this model. Therefore, the maturing rate of well-informed under-aged can be formulated as:

$$\text{MRWU} = \text{WFUPOP} \times \text{WUPOP} \times \text{FMR} \quad \text{Equation 10}$$

4.2. *Familiarity with food sharing platforms*

A crucial factor in the adoption of technology is the potential users' willingness to include it in their consideration set, which necessitates a certain level of familiarity (Struben and Sterman, 2008). Therefore, familiarity plays a key role in the diffusion of food sharing apps. The familiarity sub-system depicted in Fig. 4 draws upon the framework developed by Shams Esfandabadi (2022). Their work acknowledged the concurrent spread of multiple platforms and considered the spillover effect between these platforms, which is also suggested to be considered in the current model if multiple PSFs are competing in the market being studied. However, in our current study, our attention is primarily directed towards the diffusion of a single FSP, which holds a remarkable reputation and dominance in Italy, surpassing other similar but less extensive apps by a significant margin. Consequently, we have chosen to exclude the incorporation of the spillover effect within the presented model.

Based on Fig. 4, cumulative familiarity increases through social exposure, familiarity gaining when someone is at the replacement consideration stage, maturing the well-informed children, and the transfer of familiarity through immigration (the latter two are linked with the population sub-system discussed in section 4.1). A portion of this increase is canceled out by familiarity decrease through death and emigration of the well-informed people, loss of familiarity after making

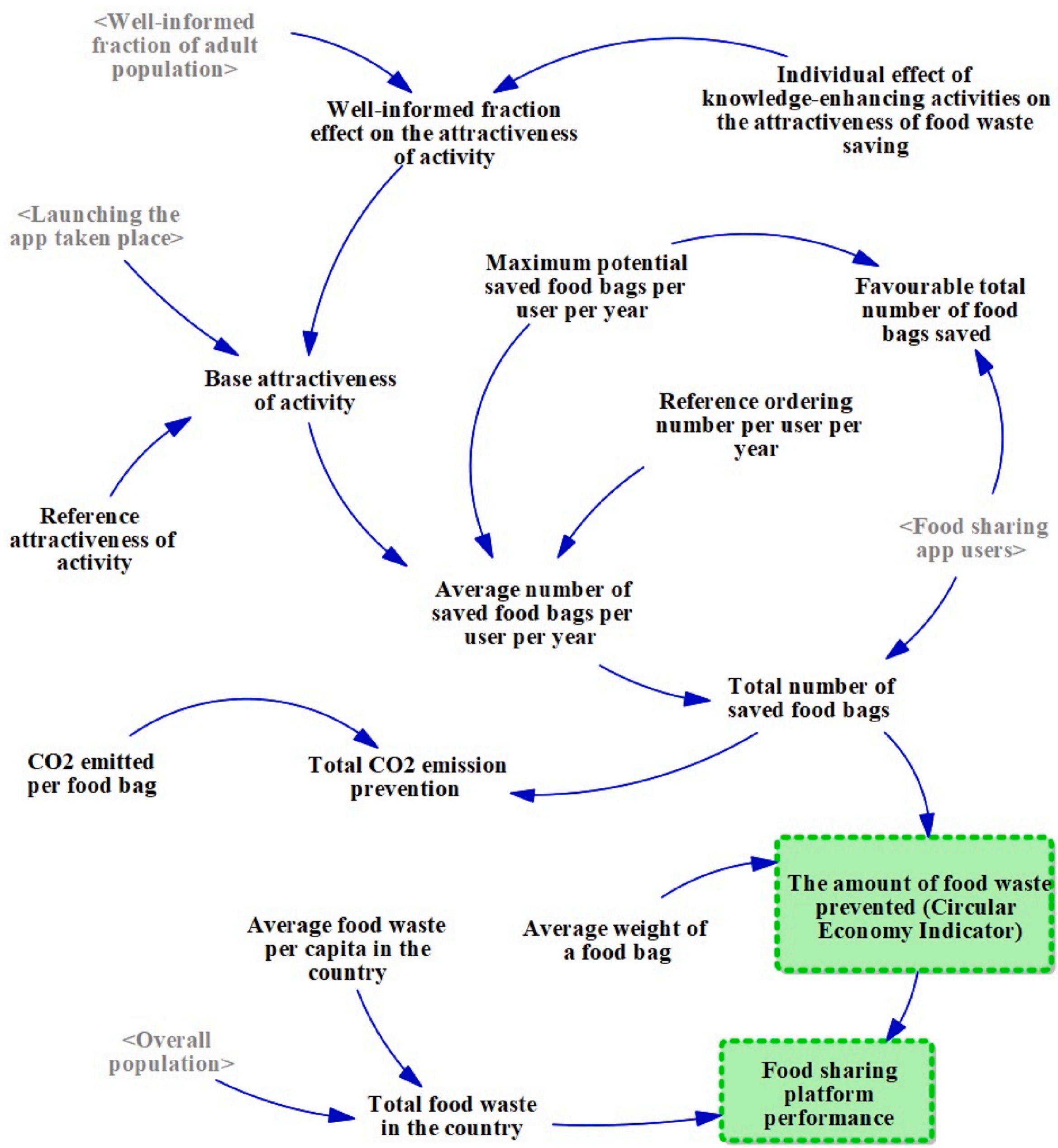

Fig. 6. Causalities linked to the estimation of FW and CO_2 emission prevention and the circularity indicator.

the adoption decision, and forgetting. On this basis, cumulative familiarity at the population level can be formulated as in Equation (11).

$$CF = \int_{t_0}^{t} (FSE + FK + FIM + FR - FDEMU - FP - FF)dt + (NU \times IF)\ (t_0) \qquad \text{Equation 11}$$

where:

CF: Cumulative familiarity.

FSE: Familiarity increase through social exposure.

FK: Familiarity increase through knowledge-enhancing activities.

FIM: Familiarity increase through immigration.

FR: Familiarity increase from replacement consideration.

FDEMU: Familiarity loss resulting from deaths and emigration of app users.

FP: Familiarity loss post adoption.

FF: Familiarity loss through forgetting.

NU: Non-users of the app.

IF: Initial familiarity.

Knowledge-enhancing activities can increase the familiarity of people with food sharing apps, hence, familiarity through knowledge-enhancing activities can be formulated as in Equation (12). Furthermore, familiarity from replacement consideration is affected by the reconsideration of the app adoption; and familiarity post adoption is estimated based on Equation (13).

$$FK = EWFAF \times (MRWU + KRAPOP) \qquad \text{Equation 12}$$

$$FP = \min\left(1, {CF}/{NU}\right) \times AD \qquad \text{Equation 13}$$

where:

EWFAF: Effect of the well-informed fraction of the adult population on familiarity.

AD: App adoption.

The familiarity increase through social exposure depends on the total social exposure and is formulated as in Equation (14).

$$FSE = TSE \times NU \times (1 - Min(1, (CF/NU))) \quad \text{Equation 14}$$

where:

TSE: Total social exposure.

Besides, total social exposure arises from marketing activities, direct word-of-mouth about the app through contacts with its users, and indirect word-of-mouth about the app with its non-users. Hence, the total social exposure can be formulated as:

$$TSE = TME + EC \times (US + ECNU \times AFE \times (1 - US)) \quad \text{Equation 15}$$

where:

TME: Total marketing effectiveness.
EC: Effective contacts.
US: Users share.
ECNU: Effective relative contacts with non-users.
AFE: Average familiarity endogenous.

4.2.1.

Total marketing effectiveness is taken into account post app launch and includes both regular marketing efforts and special marketing plans for specific periods (referred to as marketing shock in this research). On this basis, total marketing effectiveness can be formulated as:

$$TME = L \times (ME + TEMS) \quad \text{Equation 16}$$

where:

L: Launch of the app ($L = 0$ before the launch of the app and $L = 1$ after the launch of the app)
ME: Marketing effectiveness.
TEMS: Total effectiveness of the marketing shock.

The effectiveness of a regular marketing plan depends on its relative effectiveness. Besides, starting from the launch time of the app, a specific period called "honeymoon" is considered during which marketing effectiveness is not endogenous. The total effectiveness of the intensive marketing campaigns depends on their starting point, duration, and effectiveness. Multiple marketing shocks may exist in the system, depending on the market and the FSPs being studied. In order to address the dynamics related to the sharp increase in the number of TGTG users during its activity period in Italy, two sets of marketing shocks are included in the model, one to address the current intensive marketing activities (shock #1), and the other for analyzing potential scenarios (shock #2). Therefore, the total effectiveness of the marketing shock can be formulated as:

$$\begin{aligned} TEMS = {} & \text{IF THEN ELSE } (Time \\ & - \text{INITIAL TIME} < MSS1, 0, \text{IF THEN ELSE } (Time \\ & - \text{INITIAL TIME} \geq MSD1 + MSS1, 0, MSE1)) + \text{IF THEN ELSE } (Time \\ & - \text{INITIAL TIME} < MSS2, 0, \text{IF THEN ELSE } (Time \\ & - \text{INITIAL TIME} \geq MSD2 + MSS2, 0, MSE2)) \end{aligned} \quad \text{Equation 17}$$

where:

MSS1: Marketing shock 1 start.
MSS2: Marketing shock 2 start.
MSE1: Marketing shock 1 effectiveness.
MSE2: Marketing shock 2 effectiveness.
MSD1: Marketing shock 1 duration.
MSD2: Marketing shock 2 duration.

Familiarity with a technology gradually declines over time unless it is refreshed; this decay process is highly non-linear, and if exposure to the technology is infrequent and insufficient, familiarity diminishes rapidly (Struben, 2006). However, higher exposure decreases the decay rate until a highly frequent exposure is formed and familiarity decay does not continue. Hence, according to Struben (2006), familiarity loss through forgetting and fractional familiarity decay rate are formulated as follows:

$$FF = FFDR \times CF/_{TF} \quad \text{Equation 18}$$

$$FFDR = Min(1, Max(0, \varepsilon \times RRSE + 0.5 - \varepsilon \times TSE)) \quad \text{Equation 19}$$

where:

FFDR: Fractional familiarity decay rate.
TF: Time to forget.
RRSE: Reference rate of social exposure.

More details on the causalities in this sub-system can be seen in Fig. 4.

4.3. *Food sharing app adoption*

Consumer acceptance of a new technology plays a key role in its successful diffusion and sustained adoption (Struben, 2006). Therefore, the success of a digitally enabled FSP in terms of diffusion can be evaluated by considering its users. While joining a platform does not guarantee active usage of the app for ordering food bags, the absence of data to distinguish between TGTG app members and users leads to the assumption that membership equates to active app usage.

As can be seen in Fig. 5, the number of food sharing app users increases with the growth of app adoption and decreases by deaths or emigration of users and also practice reconsideration of the users. Since food is not a durable product and people can easily join and leave FSPs at any time for any reason, it is assumed that the users of such apps reconsider their membership after a while, leaving this stock. If they decide to continue using the app, they will be considered as a user again by adopting it, and if they decide to leave the platform, they become a non-user. On this basis, the following equations are formulated:

$$U(t) = \int_{t_0}^{t} (AD - PR - DEMU)dt + IU(t_0) \quad \text{Equation 20}$$

$$AD = ANU + AR \quad \text{Equation 21}$$

$$PR = U/PRT \quad \text{Equation 22}$$

$$DEMU = (SUPOP) \times (DR + EMAPOP) \quad \text{Equation 23}$$

where:

DEMU: Deaths or emigration of users.
PR: Practice reconsideration.
PRT: Practice reconsideration time.
IU: Initial app users.
ANU: Adoption by non-users.
AR: Adoption from reconsideration.
SUPOP: Share of app users from the eligible population.

The death rate and emigration of people older than 18 years of age (Emigration of adults) are linked with the population sub-system that is already discussed in section 4.1. Adoption from re-consideration by users can be formulated as:

$$AR = SA \times PR \quad \text{Equation 24}$$

where SA, referring to the "share of people adopting apps", is meant to be the share of people who have already been users of any competitive FSP, if available, who can also switch between apps. However, since only TGTG food sharing app in the Italian market is available and considered in this research, simpler forms of equations are presented and discussed. Therefore, SA can be formulated as:

$$SA = \frac{AA[\text{for users}]}{UAA + AA[\text{for users}]} \quad \text{Equation 25}$$

where:

AA: Attractiveness of the app.

UAA: Unattractiveness of the app (i.e., the reluctance of people to use food sharing apps and change their behavior regarding food consumption and wasting).

Non-users of the app have the opportunity to reevaluate their behavior within predefined time intervals and may opt to start considering its usage. Nonetheless, it is also assumed that if an individual does not choose to adopt the app within a certain number of years, they will never become a user. Hence:

$$NUC = TNU / CTNU \qquad \text{Equation 26}$$

$$CTNU = PRT \times RCTNU \qquad \text{Equation 27}$$

where:

NUC: Non-users considering the app.

TNU: Total non-users of any food-sharing app of a similar type (which is equal to NU for the considered case in this research)

CTNU: Consideration time of non-users.

RCTNU: Relative consideration time of non-users.

Furthermore, it is important to note that not all adult family members should be assumed as potential users of the food sharing app, even though they are eligible to join (older than 18 years of age). Even if all adults in a family do join the app, their individual rate of ordering food bags may be lower compared to a scenario with fewer family members as app users. Additionally, it is common for some individuals to choose not to become users of the food sharing app for various reasons. To address this, a coefficient of adoption has been incorporated into the model, allowing for a reasonable portion of the adult population to be considered as potential users. Therefore, the number of total potential users is calculated as follows:

$$TPU = APOP \times CA \qquad \text{Equation 28}$$

where:

TPU: Total potential users.

CA: Coefficient of adoption.

Similar to any other technology, the adoption of a food sharing app depends on its attractiveness to people. This attractiveness can result from the effect of the app diffusion on the perceived performance and the willingness to consider the app that is affected by the marketing activities and social exposure. Therefore, effective attractiveness for non-users of the app and attractiveness of the app are formulated as follows:

$$EANU = WTC \times AA\ [\text{for non\_users}] \qquad \text{Equation 29}$$

$$AA = BA \times e^{STP \times (1/RP - 1)} \qquad \text{Equation 30}$$

where:

EANU: Effective attractiveness for non-users of the app.

WTC: Willingness to consider the app.

BA: Base attractiveness of using the app.

STP: Sensitivity to performance.

RP: Reference performance.

Increasing people's knowledge about food sharing apps and the positive outcomes of FW prevention can increase the attractiveness of these platforms. Hence, based on Shams Esfandabadi (2022), the base attractiveness of using the food sharing app can be formulated as Equation (31), in which an increased attractiveness of using the app has been considered for the well-informed people after the FSP is launched.

$$BA = ((1 - WTFAPOP) + (WTFAPOP \times IEEA)) \times L \qquad \text{Equation 31}$$

where:

IEEA: Individual effect of education on the attractiveness of the app.

4.4. Circular economy indicator and the food sharing platform performance

According to the Circular Economy Monitoring Framework announced by the European Commission, ten overarching indicators of the CE have been categorized into five groups, including production and consumption, waste management, secondary raw materials, competitiveness and innovation, and global sustainability and resilience (European Commission, 2018). Since the focus of our research is on FW prevention at the consumption level within the food supply chain, we have considered the amount of FW prevented (corresponding to the FW indicator in the waste management category) as the main CE indicator to evaluate the performance of an FSP. The amount of FW prevented is a function of both the number of users and the amount of food they save. Therefore, the total number of saved food bags is estimated by using Equation (32).

$$TSFB = U \times ASFBPY \qquad \text{Equation 32}$$

where:

TSFB: Total number of saved food bags.

ASFBPY: average number of saved food bags per user per year.

The average number of saved food bags per user per year is affected by the attractiveness of using the app for ordering food bags. However, this number cannot always be increasing, since it is not logical to order surprise bags from food sharing apps throughout the entire year. Hence, considering an upper bound for the average number of saved food bags and using the IF THEN ELSE function of the Vensim software, this variable can be formulated as:

$$ASFBPY = \text{IF THEN ELSE}\left((BAO \times RONUP) \le MFBPY, (BAO \times RONUP), MFBPY \right) \qquad \text{Equation 33}$$

where:

BAO: Base attractiveness of activity (ordering food bags)

RONUP: Reference ordering number per user per year.

MFBPY: Maximum potential saved food bags per user per year.

Based on the causalities illustrated in Fig. 6, the attractiveness of FW prevention activities in the platform after it is launched can be formulated as:

$$BAO = (RAO + EWFAAO) \times L \qquad \text{Equation 34}$$

where:

RAO: Reference attractiveness of activity (ordering food bags)

EWFAAO: Effect of the well-informed fraction of the adult population on the attractiveness of activity (ordering food bags)

Well-informed fraction effect on the attractiveness of activity reflects the effect of knowledge enhancement among the population on the attractiveness of ordering food bags in the platform and can be formulated as:

$$EWFAAO = (1 - WFAPOP) + WFAPOP \times IEA \qquad \text{Equation 35}$$

where:

IEA: Individual effect of education on the attractiveness of the app.

To evaluate the contribution of the FSP to the CE over time, two indicators are defined and presented. First, the CE indicator, which refers to the amount of FW prevented through using the food sharing app. Second, the app's performance in terms of its contribution to the circular food system, which refers to the share of actual FW prevented through using the app to the whole FW generated at the national level. In this regard, the CE indicator and the FSP performance are calculated based on Equation (36) and Equation (37), respectively. Moreover, in order to assess the effect of the FSP diffusion and usage and provide a clear and sensible picture, in the causalities shown in Fig. 6, causal relationships have been considered to estimate the prevented CO_2 emission resulting from FW prevented.

$$CEI = AWFB \times TSFB \quad \text{Equation 36}$$

$$FSPP = \frac{CEI}{TFW} \quad \text{Equation 37}$$

where:

CEI: The circular economy indicator.
AWFB: Average weight of each food bag.
FSPP: Food sharing platform performance.
TFW: Total food waste in the country.

5. Model parameterization for TGTG in Italy

This section begins by introducing Italy's TGTG platform as the reference case. Subsequently, the key values utilized for simulating the diffusion of TGTG in Italy and its contribution to the CE are presented.

5.1. Reference case: the TGTG platform in Italy

The TGTG platform is one of the most well-known examples of food sharing for money business models worldwide. TGTG was founded in 2016 in Copenhagen and is now active in 17 countries, saving more than 250,000 meals every day (TGTG, 2022c). This platform was initiated aiming at the reduction of FW through increasing FW awareness and FW prevention by making food surpluses available to consumers. TGTG commenced operations in Italy in March 2019. By the end of 2022, 6.9 million Italians were using TGTG to order food products from 23,611 registered points of sale, resulting in saving 10 million food bags (TGTG, 2022a). Given the increasing number of users, the TGTG initiative as a successful FSP has a large presence in Italy (Fragapane and Mortara, 2022). In this regard, this platform has managed to reach over 45,000 partners, such as Carrefour, EATALY, NaturaSì, Coop Centro Italia, GROM, and Venchi 1878. Such significant achievements made by TGTG, as a successful food sharing app, can be attributed to a multitude of factors, including (i) establishing collaboration networks with a wide range of food establishments, (ii) addressing a global issue regarding the FW crisis, (iii) offering incentives and discounted prices, (iv) providing a user-friendly app and interface to connect consumers to those who supply surplus food products, and (v) building an engaged community of users.

The TGTG app allows consumers to access the list of active points of sale, mainly based on a geographical criterion for localization services. Food items on the app are usually priced between 1.99 and 4.99 euros, which is approximately one-third of their original value claimed by the points of sale. Signing up in TGTG is free for both individuals and businesses. However, businesses are required to pay an annual fee of 39 euros if they start selling the food products on the app, along with a small commission for any order based on the product price. Users can filter search results based on food availability, the pick-up time, and the type of food offered in the "Magic Box", also known as the "Surprise Bag" (referred to as food bags in this research). The interface of the TGTG mobile app is shown in Fig. 7.

TGTG activities are not limited to points of sale, such as supermarkets, bars, restaurants, etc. They also collaborate with different partners, including companies, schools, and institutions to better influence the food system and public perception of FW. As an effective action in this regard, TGTG, along with some partners, has launched an initiative named the "pact against food waste" in 2021 to ally consumer associations, businesses, and companies to fight FW more effectively. This pact outlines several solutions, including (i) providing a "conscious label" for food products to help the consumer better understand the difference between the "best before" date and "use by" date on food products, (ii) increasing the awareness and knowledge of businesses and companies regarding FW implications and FW reduction, (iii) training consumers to become more familiar with FW prevention and food consumption patterns, (iv) supporting large-scale supermarkets against FW, and (v) supporting factories to reduce FW of products left in the warehouse more effectively (TGTG, 2021). In Italy, the difference between the "best before" date and the "use by" date on food products is very subtle and often creates confusion. According to a survey, 63% of Italians misunderstand the difference between the labels "best before" date and "expiration" or "use by" date on food products (TGTG, 2022d). Hence,

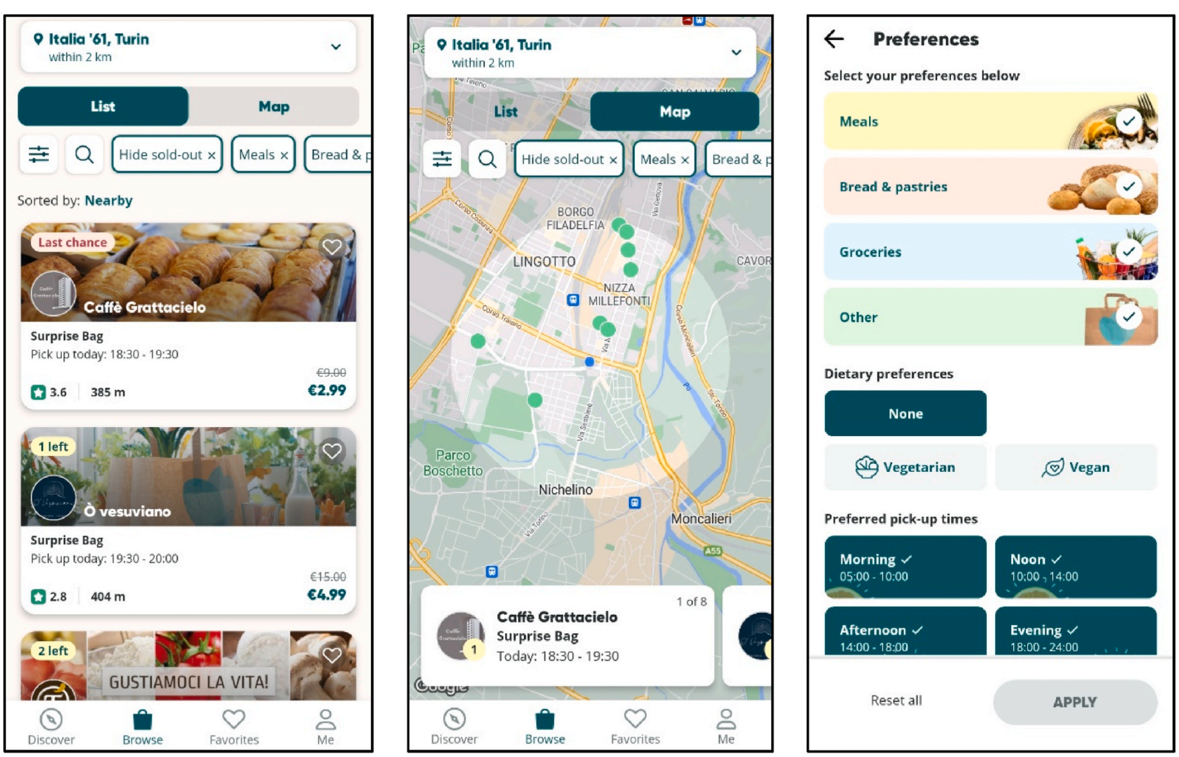

Fig. 7. The customer interface of the TGTG mobile app.

this might lead to a huge amount of FW in Italy. Moreover, incorrect interpretation of the wording on the labels of food products has contributed to 10% of FW in European countries (TGTG, 2022d).

5.2. Model parameterization

This section presents the values employed for the main exogenous variables in the base run of the model, aiming to simulate the diffusion and impact of TGTG in Italy as a reference case, showcasing the functionality of the developed model.

The initial number of well-informed populations for both under-aged and adult population stocks in the knowledge enhancement sub-system is considered zero, as there was no knowledge-enhancing program on the food sharing apps at the initial simulation time ($t_0 = 2015$). Moreover, although immigration of well-informed under-aged population and immigration of well-informed adults can potentially have a value larger than zero, for the case being analyzed in this research, these values are set to zero as the immigration of people who are already educated about FSPs is very close to or equal to zero.

The initial values of the population stocks, referring to the people aged 0-17 years and adults of more than 18 years of age in 2015, were set based on the available data on PopulationPyramid (2022), equal to approximately 9,783,272 and 50,795,216 people, respectively, summing up to an overall population of 60,578,488. The overall population of Italy at the beginning of 2022 was 59,030,133, consisting of 9,218,914 people less than 18 and 49,811,219 people with at least 18 years of age (ISTAT, 2022), and it is projected that the population will experience a reduction by 2060. Based on the available population projections in Italy, in 2060 the population of this country will be in a range from approximately 46 to 56 million, with a lower limit of 90% of 46,151,752, a median of 50,905,715, and an upper limit of 90% of 56,053,197 (ISTAT, 2022). Therefore, the population parameters are set in a way that the model generates a decreasing trend in the overall population close to the observed trend from 2015 to 2022 in Italy and the projected population for 2060.

Since TGTG was not yet launched in Italy during the initial simulation time (t_0) in 2015, the initial number of app users in Equation (20) is set to zero. Furthermore, to address the number of TGTG app users over time, reference was made to the available data as of the end of 2022 in Italy (TGTG, 2022a). Accordingly, the model was populated in a manner that approximates a simulated user count of approximately 6.9 million people by 2022.

To estimate the volume of the FW prevented and its subsequent prevention in CO_2 emission, in line with the TGTG impact report of 2021 (TGTG, 2022e), the average weight of each food bag is assumed to be 1 kg, whose saving helps prevent 2.5 kg of CO_2e. Besides, certain assumptions have been made regarding the average number of saved food bags per user per year, which is an endogenous variable in the model. According to the website of TGTG (TGTG, 2022a), by the end of 2022, 6.9 million people used the TGTG app in Italy and saved 10 million food bags. As the number of saved food bags is cumulative over approximately 4 years, the average number of saved food bags per user per year has been assumed to be 0.36 (i.e. $\frac{10\ million}{6.9\ million}/4$) in 2022, and the model is calibrated such that the simulated value corresponding to this variable approaches the estimated value. Table 1 presents the values used for

Table 1
Values used for the main exogenous variables in the model to simulate the diffusion and impact of TGTG FSP in Italy.

Variable	Unit	Value	Reference/Justification
Under-aged population in 2015	Person	9,783,272	Estimation based on PopulationPyramid (2022)
The population of adults in 2015	Person	50,795,216	Estimation based on PopulationPyramid (2022)
Fractional birth rate	$^{1}/_{year}$	0.007	Estimation based on I.Stat (ISTAT, 2022)
Fractional death rate	$^{1}/_{year}$	0.0134	Estimation based on I.Stat (ISTAT, 2022)
Fractional immigration rate of under-aged population	$^{1}/_{year}$	0.004	Estimation based on I.Stat (ISTAT, 2022)
Fractional immigration rate of the adult population	$^{1}/_{year}$	0.004	Estimation based on I.Stat (ISTAT, 2022)
Fractional emigration rate of under-aged population	$^{1}/_{year}$	0.003	Estimation based on I.Stat (ISTAT, 2022)
Fractional emigration rate of the adult population	$^{1}/_{year}$	0.0035	Estimation based on I.Stat (ISTAT, 2022)
Normal time to educate children	Year	10	Assumption
Normal time to educate adults	Year	10	Assumption
Launch time lag	Year	4	TGTG was launched in 2019, while the simulation period starts in 2015.
Honeymoon duration	Year	10	Assumption
Effective relative contact with non-users	dimensionless (*dmnl*)	0.25	Struben (2006)
Effective contacts	$^{dmnl}/_{year}$	0.3	Struben (2006)
Reference rate of social exposure	$^{1}/_{year}$	0.05	Struben (2006)
Normal marketing effectiveness	$^{dmnl}/_{year}$	0.01	Model calibration
Time to forget	Year	1	Assumption
Familiarity of immigrants	$^{Person}/_{year}$	0	Assumption
Practice reconsideration time	Year	1.5	Assumption
End of the decision period	Year	50	Assumption
Co-efficient of adoption	*dmnl*	0.8	Assumption
The unattractiveness of the app	*dmnl*	1.2	Heuristics and model calibration
Reference performance	*dmnl*	1	Assumption
Sensitivity to performance	*dmnl*	1.5	Assumption and model calibration
Individual effect of knowledge enhancement on the attractiveness of the app	*dmnl*	2.5	Assumption and model calibration
Average FW per capita in the country	$^{kg}/_{person * year}$	31	The amount of FW per capita in Italy is estimated to be 595.3 gr per week (WWIO, 2022)
The individual effect of knowledge enhancement on the attractiveness of FW saving	*dmnl*	2	Model calibration
Reference ordering number per user per year	$^{bag}/_{person * year}$	1	Assumption
Reference attractiveness of activity	*dmnl*	0.3	Assumption and model calibration

other main exogenous variables.

The validity of an SD model is contingent upon its ability to successfully pass tests that demonstrate its soundness, defensibility, and grounding, aligning it with the specific objectives for which it was designed (Coyle and Exelby, 2000). The validation of an SD model is an ongoing process aimed at both testing and fostering confidence in the model's reliability (Sterman, 2000). This comprehensive validation process can be broadly conceived as an endeavor to establish that both the model's structure and its behavior are consistent with the existing knowledge about the studied system (Homer, 2012). It is imperative to note that validation should not be delayed until the model's completion, but rather, confidence in its utility should be incrementally developed (Sterman, 2000).

SD modelers employ a diverse array of tests to evaluate and enhance their models, covering flaws. These tests include but are not limited to boundary adequacy, structure assessment, parameter assessment, dimensional consistency, extreme conditions, behavior reproduction, behavior anomaly, surprise behavior, and sensitivity analysis (Sterman, 2000).

In the context of the model developed for this research, the boundary adequacy test has been diligently conducted, referring to the designed model's boundary chart, stock-flow diagrams, and the model equations, assuring that essential concepts for addressing the problem in this research are endogenous to the model. Additionally, the dimensional consistency of the model has been assessed by scrutinizing the units of parameters in the equations, ensuring their conformity and relevance to real-world concepts. Furthermore, both the parameter assessment and extreme conditions testing yielded satisfactory results.

The structure and behavior of the model are tested by conducting partial model tests and evaluating the behavior of the whole model. Partial model tests serve to gauge the intended rationality of decision rules (Homer, 2012). In this context, a thorough examination of the key variables, including FSP users, familiarity, population, and trained people, has been undertaken to validate the model's efficacy.

6. Simulation results and discussion

Given that TGTG commenced operations in Italy in 2019, the simulation's initial time is set at 2015 to accommodate a warm-up phase and capture the diffusion dynamics from the early stages. Furthermore, to facilitate a comprehensive analysis of the system's behavior under various policy scenarios over time, the simulation time extends up to 2060. The sustained diffusion of the app, as demonstrated by the observed system behavior outlined in this section, justifies the chosen time span as appropriate.

Between the years 2019 and 2022, a remarkable surge in the number of TGTG users is evident. Evidence shows that very intensive social media and marketing support has led to such an increase in the number of users. Hence, in addition to the regular marketing programs that companies follow, a strong marketing campaign has been considered in the base run to simulate the current trend of the TGTG app users. Besides, although no report is available on specific knowledge-enhancing activities for children regarding food sharing apps in Italy, the TGTG pact (TGTG, 2021) does outline training activities for staff of supermarkets, companies, and different points of sales. Therefore, an active knowledge-enhancing program for adults has been incorporated in the base run.

The duration and effectiveness of marketing activities play a crucial role in ensuring the successful diffusion of products and technologies over time. These factors are influenced by various elements, including budget, target audience, market competition, product nature, and overall marketing strategy employed by the organization (Mela et al., 1997). In the base run, we have incorporated a comprehensive marketing campaign that commenced in 2019, exhibiting a relatively high effectiveness of 0.05. Given the absence of a specific estimate for the duration of TGTG's intensive marketing activities, we have assumed a duration of 10 years to assess the impact of this marketing shock (i.e., until 2029). Moreover, a 15-year timeframe commencing from 2021 has been taken into account for knowledge-enhancing activities targeting the adult population. These activities align with the "pact against food waste" initiative and are assumed to have a relatively low effectiveness of 0.2 in the baseline. Although the period of the training program is not stated in any report, the training period is limited to 15 years to better analyze the dynamics of the system. Analysis shows that the highest level of marketing shock effectiveness is 0.06 and the maximum effectiveness for knowledge-enhancing programs can reach up to 1.

In the following sub-sections, potential scenarios to improve the environmental indicators, as well as the number of users, are analyzed and discussed. Finally, the best potential scenario is recommended.

6.1. Bolstering marketing campaigns

To test the effect of marketing efforts on the number of TGTG users, the performance of TGTG, and the CE indicator, three different potential scenarios are considered. To this end, an additional marketing shock, according to the described criteria in Table 2, is added to the already active marketing and knowledge-enhancing activities in the base run. Due to the importance of duration, starting point, and effectiveness of the marketing, different starting times and durations are tested in these scenarios. In this regard, the effectiveness of the additional marketing campaign is set to the maximum.

According to the simulation results shown in Fig. 8(a), starting marketing efforts late (2030) does not considerably change the dynamics of the number of users in comparison with the base run. While initiating the additional campaign earlier may have a minimal impact, the duration of the campaign does not significantly influence the outcome as the market is already saturated. Besides, although a slight decrease in the trend is observed after around 2036, which is because of the end of the knowledge-enhancing program assumed in the base run, the market is considered a successful market in terms of the number of users as it is expected to follow an s-shaped curve and become sustained after around 2040. The simulated number of users in 2060 in the base run is approximately 17,524,100. This shows that the TGTG marketing campaign is already performing very effectively. This can be confirmed by the available data regarding the significantly increasing number of TGTG users over its few years of activities in Italy.

There might be several potential reasons for such a fast growth in the number of TGTG app users. First, it is very easy to join and use the app. Unlike many other technologies and products, potential new users can easily access the app and install it on any device for free. Second, TGTG's social exposure seems to be high and effective. The current marketing efforts of TGTG have led to increasing social exposure for potential users. The reinforcing loop shown in Figs. 1 and 4 indicates this positive effect. In this vein, marketing increases total social exposure, then, social exposure leads to familiarity increase, and accordingly, when familiarity goes up, word-of-mouth among people regarding the TGTG app rises. Therefore, effective contact between people leads to an increase in total social exposure again, creating a positive loop within the system. Based on the developed model, this loop is working properly and shows the significant role of effective marketing in increasing the number of TGTG users. TGTG has a large existence in social media, news, the press, and social events. For instance, Time magazine introduced TGTG as one of the Time's 100 influential companies in 2022, and Vo-Thanh et al. (2021) identified TGTG as the largest social movement in Europe

Table 2
Potential scenarios tested regarding extra marketing activities (in addition to the current marketing campaign).

Scenario	Starting time	Duration (year)	Effectiveness
M1	2023	10	0.06
M2	2023	30	0.06
M3	2030	20	0.06

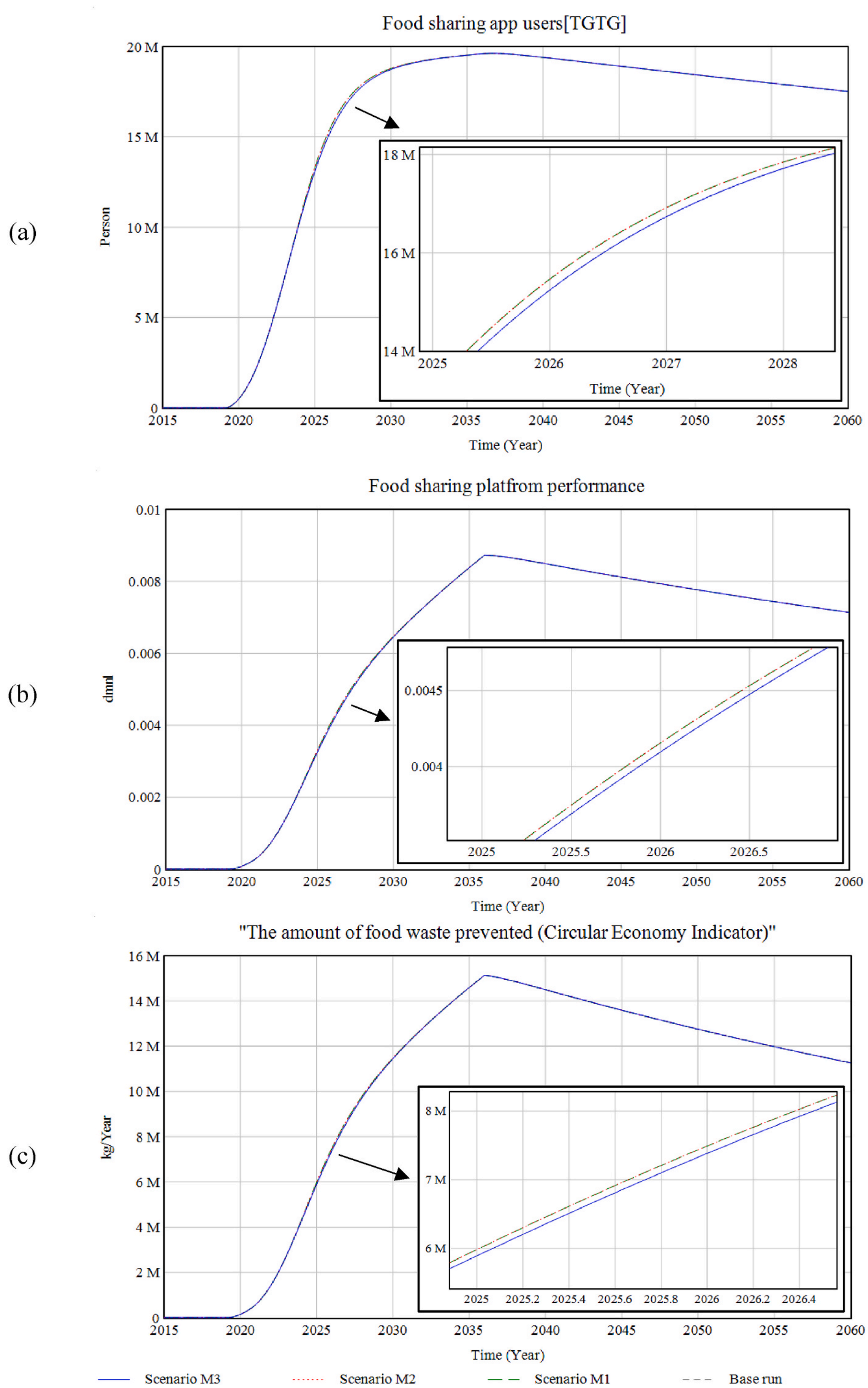

Fig. 8. The effect of extra marketing shock scenarios on the number of TGTG users (a), FSP performance (b), and CE indicator (c).

dedicated to fighting FW. Moreover, the TGTG app ranked 10th among the most downloaded apps in the food and beverage industry in the world, highlighting the significant attention gained by this FSP (TGTG, 2022e).

As shown in Fig. 8(b) and (c), applying extra marketing efforts as in scenarios M1, M2, and M3 does not have a significant impact on TGTG performance and the CE indicator, and the changes are very tiny. The main reason for this tiny change is that marketing affects the attractiveness of joining the app, and hence, does not increase the average number of food bags saved by each user significantly. On this basis, since extra marketing efforts (in addition to what already exists in the base run) do not make considerable changes in the number of TGTG users, they cannot significantly affect the CE indicator and the platform performance. Therefore, keeping the current marketing profile of TGTG seems to be sufficient for its success in terms of the number of users, but further attempts should be made via other means to improve the CE indicator and leverage the platform performance in fighting against FW in Italy.

6.2. *Knowledge-enhancing programs for adults*

A comparison between the total number of users at the end of 2022

(6.9 million) with the total food bags saved since 2019 (10 million) (TGTG, 2022a) shows that a huge number of users are not using the app. According to Pisoni et al. (2022), a survey conducted on TGTG users revealed that a significant proportion of individuals who have signed up for TGTG do not follow through with making a purchase. However, when people are educated about the FSPs and related subjects, such as the best time to consume and the expiry date of the food products, not only do they become interested in joining the app, but also, they are more motivated to use the app by ordering food bags. More food bag ordering per user in the platform increases the amount of FW prevented, which consequently improves the performance of the app, and also prevents a higher amount of CO_2 emission.

In order to analyze the effect of knowledge enhancement among the adult population on the behavior of the key variables and indicators in the model, the potential changes in the knowledge-enhancing activities have been analyzed in three categories of scenarios. First, what if the currently active training activities for adults (based on the TGTG's pact) continue for an extended period? In the base run, the duration of these training activities has been assumed to be 15 years. Hence, the potential dynamics resulting from continuing these knowledge-enhancing activities with the same effectiveness for longer periods are compared with the base run. Second, what if the current training effort is kept as assumed in the base run (from 2021 to 2036), but an extra knowledge-enhancing effort is added to it as soon as possible (starting from 2023)? Third, what if the current training efforts are kept for an extended period (for 30 or 40 years instead of 15 years) and extra knowledge-enhancing efforts are added to it as soon as possible (starting from 2023)?

6.2.1. *Keeping the current knowledge-enhancing activities for an extended period*

In this set of scenarios, the existing training activities already included in the "pact against food waste" initiative launched by TGTG in 2021 are kept unchanged over an extended period of 30 and 40 years, instead of 15 years. Continuing knowledge-enhancing programs for adults leads to an increase in the number of well-informed adult population. Therefore, with the increase in the well-informed adult population, the number of food sharing app users goes up. As shown in Fig. 9 (a), the number of users starts to decrease from 2038 in the base run. In this regard, continuing the current training effort for 30 years (scenario KA1) increases the number of users until 2051 but decreases it from 2051 onwards. This is while keeping the current activities for 40 years (scenario KA2) can sustain the market. The slight decrease near 2060 is due to the decrease in population in Italy based on the available projections (ISTAT, 2022).

The base run shows that the average number of saved food bags per user per year is 0.36 of a food bag in 2022. According to the model,

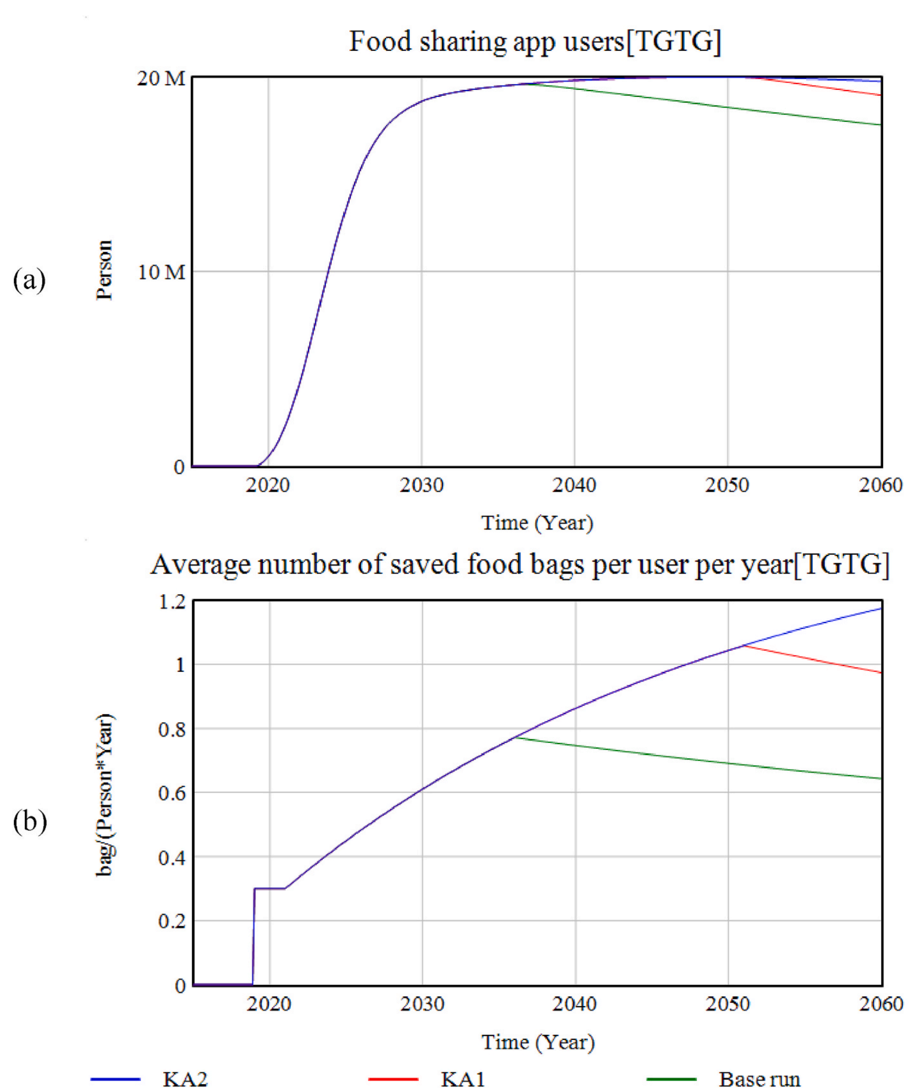

Fig. 9. The effect of keeping the current knowledge-enhancing activities for adults for a long time on the number of TGTG users (a) and the average number of saved food bags per user per year (b).

knowledge-enhancing activities and plans positively affect the attractiveness of using the food sharing app to make orders and accordingly save more food products. Hence, as shown in Fig. 9(b), knowledge-enhancing programs have a significant impact on the number of saved food bags. For instance, the base run, which includes a 15-year training plan starting from 2021, shows a continuously increasing trend in the average saved food per user. However, once the training stops in 2036, the average saved food per user starts decreasing. In this vein, 30 years of training activities for adults leads to a continuous increase in the average saved food by 2051, reaching an average number of 1.059 saved

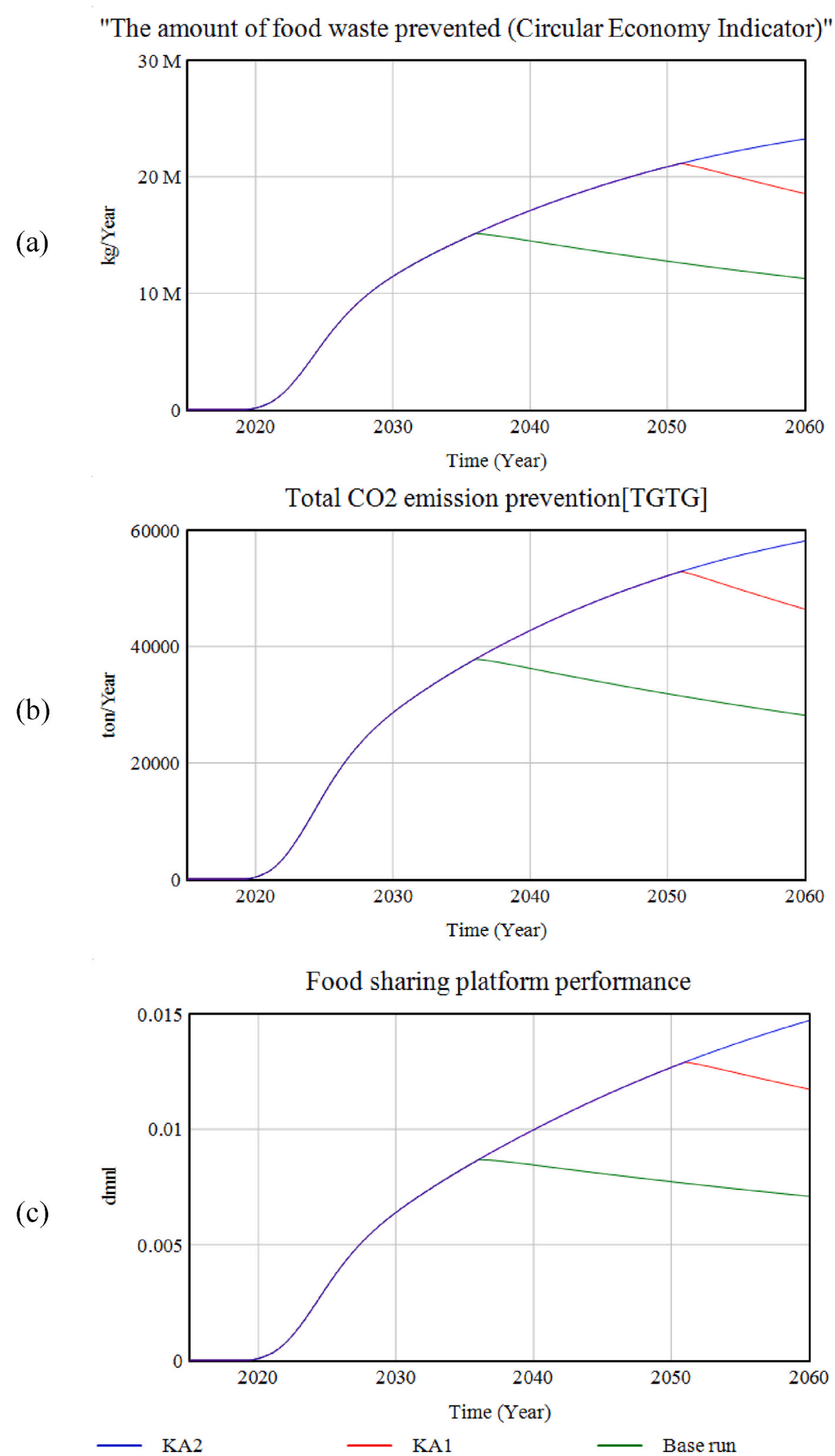

Fig. 10. The effect of keeping the current knowledge-enhancing activities for adults for a long time on the amount of FW prevented (the CE indicator) (a), the total CO_2 emission prevention (b), and TGTG performance (c).

food bags per user per year. According to Fig. 9(b), continuing the current knowledge-enhancing activities constantly increases the average number of annual saved food bags per user by 2060, reaching around 1.8 bags per user, which is a significant improvement compared to the base run.

Implementing each of the described scenarios shows a positive outcome in terms of the contribution to the CE through the amount of FW prevented in TGTG. As illustrated in Fig. 10(a), scenario KA2 can be more effective in terms of the amount of FW prevented. In this regard, the amount of FW prevented increases constantly by 2060, reaching 23,246,200 kg. This is while the base run scenario will lead to a decrease in the amount of FW prevented from 2036 to 2060 due to the lower level of knowledge-enhancing activities compared to the longer-term knowledge-enhancing efforts. Besides, scenario KA2 results in a continuous reduction of CO_2 emissions by 2060, reaching more than 58,000 tons of CO_2 emission prevented per year in 2060. Hence, long-term training plans significantly influence food resource efficiency and the environment towards a CE transition in the food sector. Accordingly, since the amount of FW prevented is increased by continuing the knowledge-enhancing activities, the performance of the app improves continuously, as shown in Fig. 10(c).

6.2.2. Adding extra efforts to the current knowledge-enhancing activities

The scenarios introduced in Table 3 maintain the current training effort in the base run while incorporating additional knowledge-enhancing efforts of varying durations. All scenarios start from 2023 as analyses show that the earlier knowledge-enhancing activities start, the higher the number of well-informed people over time would be; hence, the system can be more successful. Three levels of knowledge-enhancement effectiveness, including 0.2, 0.5, and 0.8, are considered to test different scenarios. In scenarios KA3 and KA6, the effectiveness of the extra knowledge-enhancing programs is equal to the effectiveness of the currently active training efforts in the base run (0.2).

While increasing the duration of already active training activities leads to continuing almost the same trend for the number of users (as shown in Section 6.2.1), adding extra knowledge-enhancing programs to the current attempts changes the slope of the lines in comparison with the base run (Fig. 11(a)). Moreover, the greater the effectiveness of knowledge-enhancing activities, the steeper the slope of the lines representing the dynamics of well-informed individuals and food sharing app users. Starting from 2036, when the current training program (in the base run) ends, a slight decrease in the number of users is observed. Comparing the dynamics resulting from each pair of scenarios with similar training effects shows that keeping the extra knowledge-enhancing programs for a longer period is more effective in keeping the number of users as high as possible. In any case, adding extra knowledge-enhancing activities to the current situation can increase the number of users in comparison with the base run. Furthermore, the average number of saved food bags per user is affected by knowledge-enhancing programs and, hence, increases accordingly. From 2019 to 2021, the average number of food bags saved per user is assumed constant. By starting training efforts in 2021 based on the TGTG's pact, there is an increase in the average number of food bags saved per user. If extra knowledge-enhancing efforts are put into force for adults starting from 2023, a sharper increase in the number of average bags saved per user will be achieved (Fig. 11(b)), which is favorable. Hence, as the additional knowledge-enhancing efforts increase in both intensity and duration, the average number of food bags saved per user also increases.

Table 3
Scenarios regarding adding extra knowledge-enhancing efforts for adults to the base run.

Scenario	Starting time	Duration (year)	Effectiveness
KA3	2023	30	0.2
KA4	2023	30	0.5
KA5	2023	30	0.8
KA6	2023	40	0.2
KA7	2023	40	0.5
KA8	2023	40	0.8

As Fig. 12(a) illustrates, increasing knowledge-enhancing activities for adults makes significant changes in the total amount of FW prevented compared to the knowledge-enhancing activities in the base run. In this regard, while the amount of FW prevented starts to decrease in 2036 (ending time of knowledge-enhancing activities in the base run), a lengthier knowledge-enhancing program and a higher level of effectiveness in knowledge enhancement activities lead to a higher amount of FW prevented. Scenario KA8 with a duration of 40 years and effectiveness of 0.8 leads to the highest FW prevention by TGTG, reaching 44,313,200 kg of annual prevented FW in 2060. This is while the base run scenario reaches 11,272,400 kg of FW prevention in 2060, which is almost four times smaller than the amount prevented by scenario KA8. The significant difference between scenario KA8 and the base run scenario regarding FW prevention denotes the critical role of additional knowledge-enhancing programs and plans to foster the CE transition and FW prevention. Accordingly, the total CO_2 emission prevention shows approximately similar dynamics on a different scale (Fig. 12(b)). Although the FSP performance (Fig. 12(c)) seems to have similar dynamics to the CO_2 emission prevention and the CE indicator, the slope of the curve at different points of time for this indicator is different from the other two indicators. The main reason for this difference is that the platform performance reflects the share of FW prevented by the platform from the total FW in Italy, while the CE indicator and the CO_2 emission prevention are a multiplication of the total number of food bags saved.

6.2.3. Extensive knowledge-enhancing programs for adults

In this section, alongside the current training efforts active for 40 years (referring to Section 6.2.1), supplementary knowledge-enhancing efforts are introduced (referring to Section 6.2.2) to observe the dynamics of the key variables. In this vein, three scenarios, as described in Table 4, are analyzed.

Within this set of scenarios, the population of well-informed adults surpasses the numbers observed in the two previously analyzed sets, owing to the extensive and prolonged knowledge-enhancing efforts specifically targeted at the adult population. However, as can be seen in Fig. 13(a), the higher the effectiveness of the extra training program, the lower the slope of the well-informed adult population after 2050. This highlights that if knowledge-enhancing programs in place are adequately high, a greater number of people are educated at an earlier time, and a lower number of people remain to be well-informed later. This is advantageous for the entire society, particularly in terms of promoting technologies that facilitate the transition towards CE and sustainability.

Consistent with the larger population of well-informed individuals in scenario KA11, which has the highest level of effectiveness of knowledge enhancement activities, this scenario also demonstrates the highest number of app users (Fig. 13(b)). A clear s-shaped curve can be seen in this figure in all three presented scenarios, highlighting the success of the app in the market in terms of the number of users. As depicted in Fig. 13 (c), there is a rise in the average number of food bags saved from 2021 to 2023, attributed to knowledge-enhancing programs aligned with the current activities included in the TGTG's pact. From 2030 onwards, the increase in the average number of saved food bags is influenced by both the current training efforts that last until 2063 and additional knowledge-enhancing initiatives during this period. Consequently, as anticipated, the average number of food bags per user per year in 2060 within this scenario surpasses the numbers presented in Fig. 11(b), exceeding a noteworthy 2 saved food bags per user. This substantial increase, from 0.36 in 2021 to more than 2.04 in 2060, holds great promise.

Accordingly, the amount of FW prevented, the total CO_2 emissions prevented, and TGTG performance are positively influenced by accounting for additional knowledge-enhancing activities. For instance,

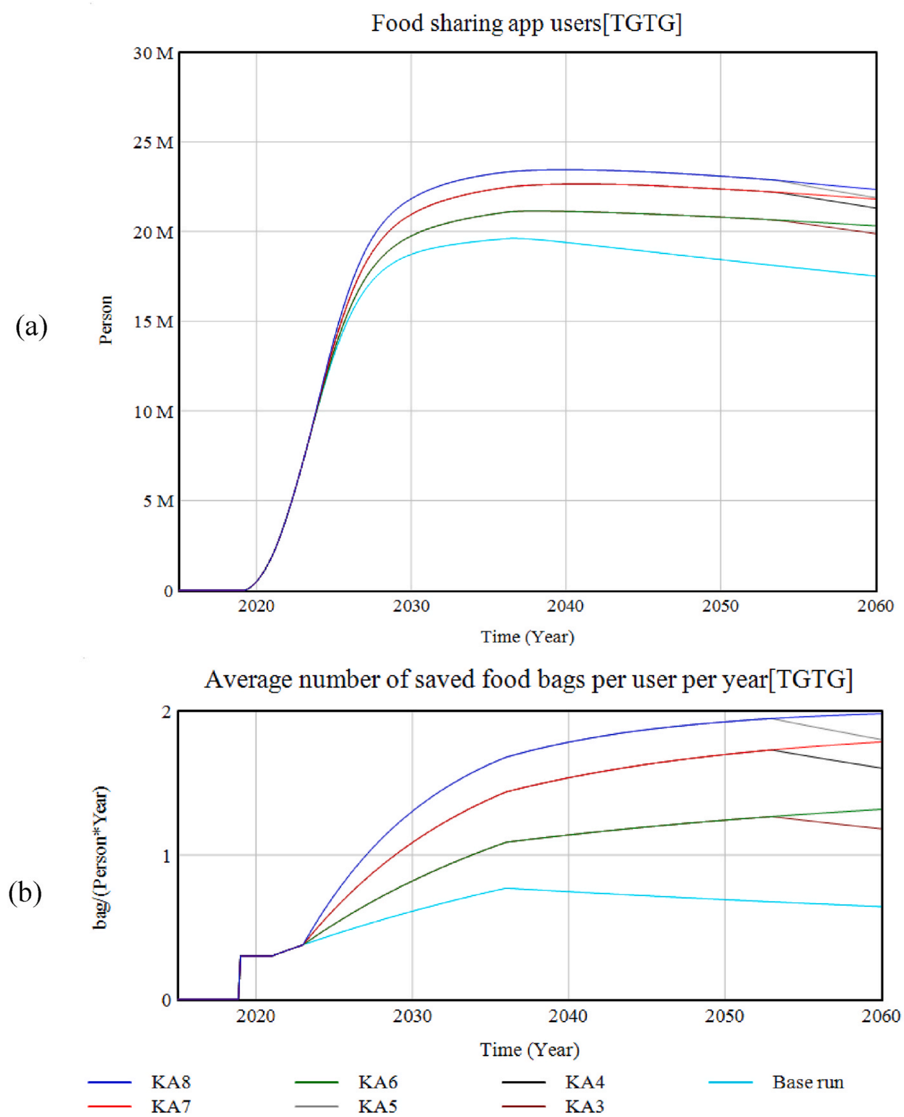

Fig. 11. The effect of adding extra knowledge-enhancing efforts for adults to the base run on the number of TGTG users (a) and the average number of saved food bags per user per year (b).

scenarios KA11, KA10, and KA9 result in 46,010,200, 42,338,900, and 34,153,600 kg of FW prevented per year in 2060, while this amount in the base run is 11,272,400 kg per year in 2060 (Fig. 14(a)). Hence, the performance of TGTG experiences a substantial improvement, reaching 0.029 in 2060 within scenario KA11, in comparison with the base run that yields a value of 0.007 in 2060 (Fig. 14(c)). It is important to highlight that while the curve representing scenario KA11 in Fig. 14(a) and (b) appears to flatten out after around 2050, this scenario still maintains a positive impact on the FSP performance due to the continuous increase in the average number of annual food bags saved per user.

Analyzing these scenarios highlights the significant role of knowledge enhancement among adults in improving (i) the number of users, and (ii) the amount of saved food bags per user per year, which leads to enhancing the performance of the food sharing app, and accordingly, FW and CO_2 emissions prevention. Unlike the marketing campaign, which is adequately in place and works effectively, knowledge-enhancing programs and activities should be strengthened to contribute to the CE and FW prevention more effectively.

6.3. Knowledge-enhancing programs for children

Since there is no adequate report on training activities in schools in Italy, this section assumes that no substantial training has been conducted for the under-aged population in this context so far. Consequently, knowledge-enhancing activities for individuals under the age of 18 regarding food sharing are initiated in 2023.

The model considers knowledge enhancement for the entire population under the age of 18, extending beyond children in schools. Besides, as mentioned in Section 4.1, the assumption of perfect mixing applies to all stocks in the model, addressing an equal chance for all under-aged individuals to receive training. Therefore, a significant amount of time is required for knowledge enhancement among the under-aged population to observe a consistent trend of increasing the number of well-informed adults. Based on this premise, various scenarios analyzing knowledge enhancement among the under-aged population are examined, as reported in Table 5.

Fig. 15(a) shows the effect of the introduced scenarios regarding knowledge enhancement among under-aged on the number of well-informed adults. These scenarios are applied to the base run of the model. Therefore, as can be seen in Fig. 15(a), there is a sharp increase in the number of well-informed adults by 2036, which is mainly due to knowledge enhancement among adults during this period. During this period, the impact of training and educating children on the slope of this line is relatively minimal. This is due to the time required for well-

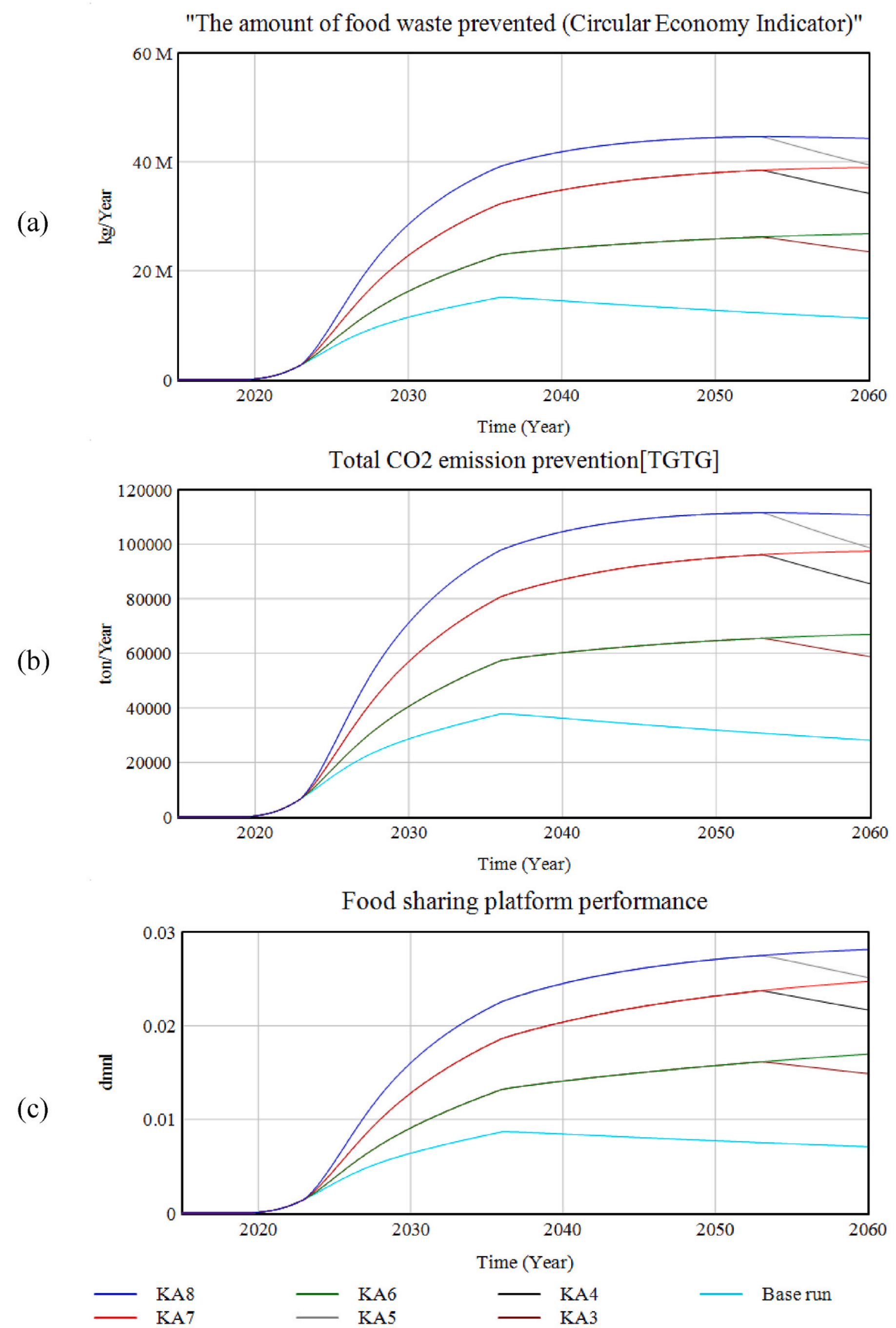

Fig. 12. The effect of adding extra knowledge-enhancing efforts for adults to the base run on the amount of FW prevented (the CE indicator) (a), the total CO_2 emission prevention (b), and TGTG performance (c).

Table 4
Scenarios regarding adding extra knowledge-enhancing efforts for adults to the base run.

Scenario	The starting time of the additional program	Duration of the additional program (year)	Effectiveness of the additional program
KA9	2023	40	0.2
KA10	2023	40	0.5
KA11	2023	40	0.8

informed children to transition into well-informed adults who can actively participate in and utilize the platform. Consequently, the effect of training and education among children is not immediately reflected in the increase of well-informed adults joining the platform. After 2036, a sharp decrease in the number of well-informed adults is observed in all scenarios. However, scenarios with higher knowledge enhancement effectiveness for children result in a higher number of well-informed adults. Besides, as expected, the number of well-informed adults begins to decline after the conclusion of the 30-year knowledge-enhancing program.

Fig. 15(b) denotes the effect of knowledge enhancement among children on the number of app users. While scenarios with higher effectiveness of knowledge enhancement lead to a greater increase in the

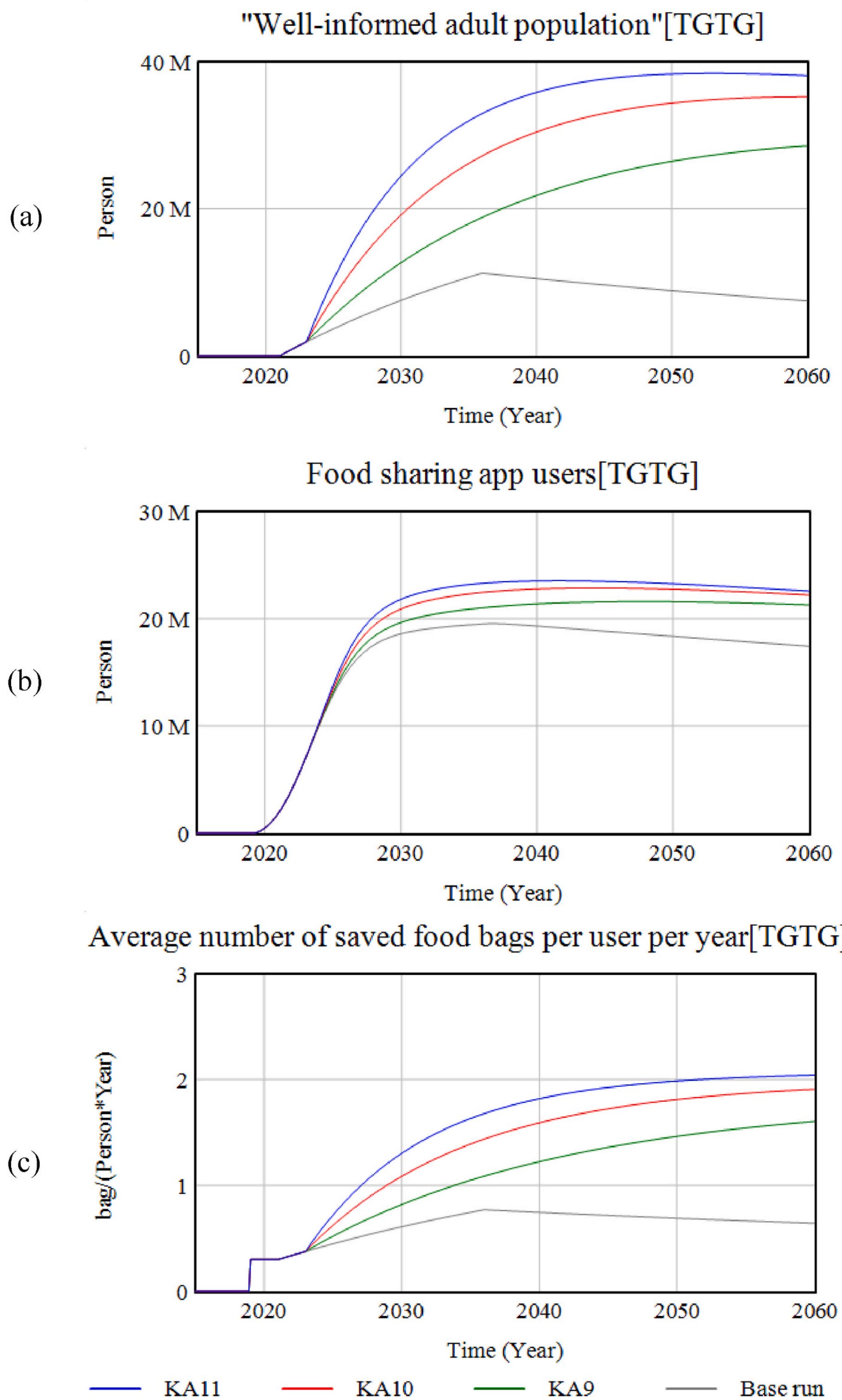

Fig. 13. The effect of extensive knowledge-enhancing programs for adults on the number of the well-informed adult population (a), the number of TGTG users (b), and the average number of saved food bags per user per year (c).

number of well-informed adults, the corresponding increase in the number of users is not as pronounced. This is because (i) not all well-informed people decide to use the app, and (ii) some of the well-informed population might already be a member of the platform. Hence, the increase in the number of well-informed adults is not proportional to the increase in the number of users. Moreover, as Fig. 15(b) shows, the results of keeping knowledge-enhancing activities for children in place for 30 and 40 years are very close to each other in terms of the number of users. Regarding the average number of saved food bags per user, similar dynamics as the dynamics in well-informed adults are observed but with a different scale. Knowledge enhancement among children in each of the mentioned scenarios improves the number of average food bags saved per user in comparison with the base run (Fig. 15(c)).

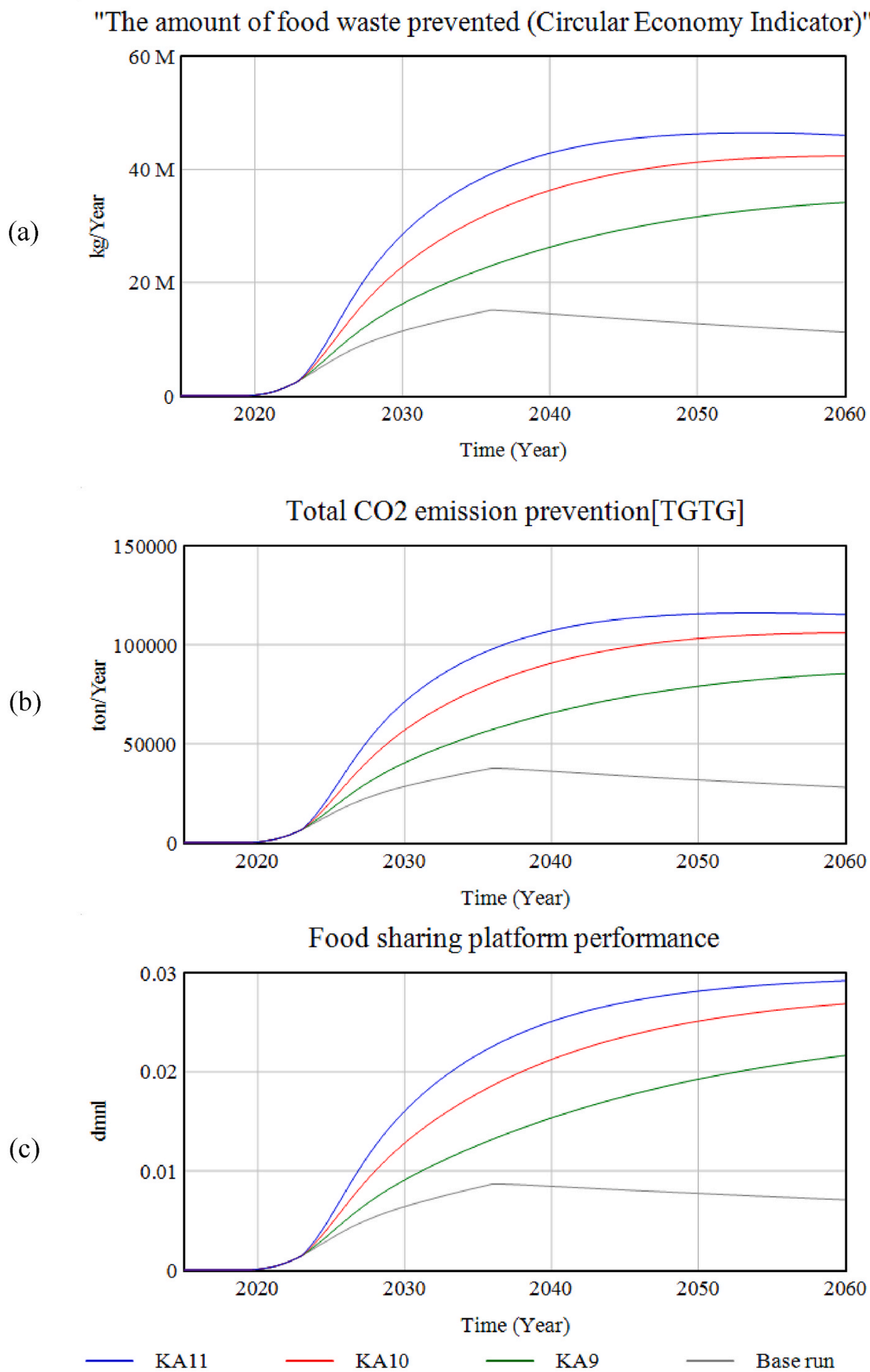

Fig. 14. The effect of extensive knowledge-enhancing programs for adults on the amount of FW prevented (the CE indicator) (a), the total CO_2 emission prevention (b), and TGTG performance (c).

Table 5
Scenarios regarding knowledge enhancement among the under-aged population.

Scenario	Starting time	Duration	Effectiveness
KU1	2023	30	0.2
KU2	2023	30	0.5
KU3	2023	30	0.8
KU4	2023	40	0.2
KU5	2023	40	0.5
KU6	2023	40	0.8

As a result, although knowledge enhancement regarding FW and FSPs among children is effective and may help improve the indicators in the model in the long term (see Fig. 16), its effect on the system is not as much as knowledge enhancement among adults by 2060. However, since children are future potential users of the app, knowledge enhancement among children must be taken into account as already noticed in the TGTG's pact against FW.

6.4. *Policy recommendation and analysis*

Analysis in Section 6.1 showed that the current marketing campaign

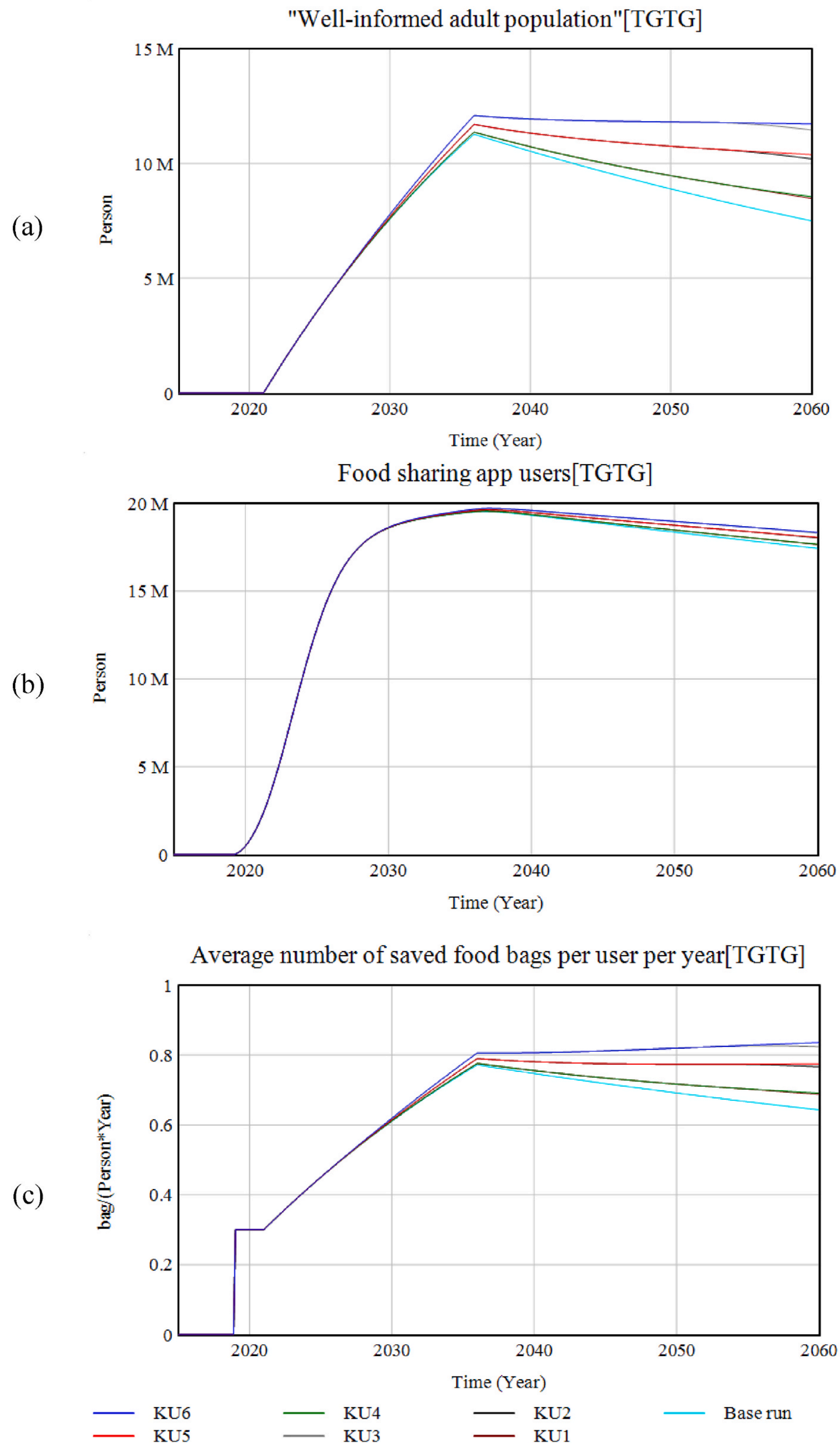

Fig. 15. The effect of knowledge enhancement among the under-aged population on the well-informed adult population (a), the number of TGTG users (b), and the number of saved food bags per user per year (c).

for TGTG is strong, adequate, and effective. Hence, keeping this marketing force active for almost 10 years, as in the base run simulation, can result in a successful market for this rapidly growing app in terms of the number of users. However, in addition to the number of users, the amount of FW prevented by this app should be taken into account when evaluating its success. Analyzing scenarios regarding training adults and the under-aged population in Sections 6.2 and 6.3 revealed that longer-period and more effective knowledge-enhancing programs can still increase the number of app users by increasing their knowledge about the food sharing app and its positive impact on the environment and transitioning towards a CE. More importantly, effective knowledge-enhancing programs can encourage the app users to use the app more

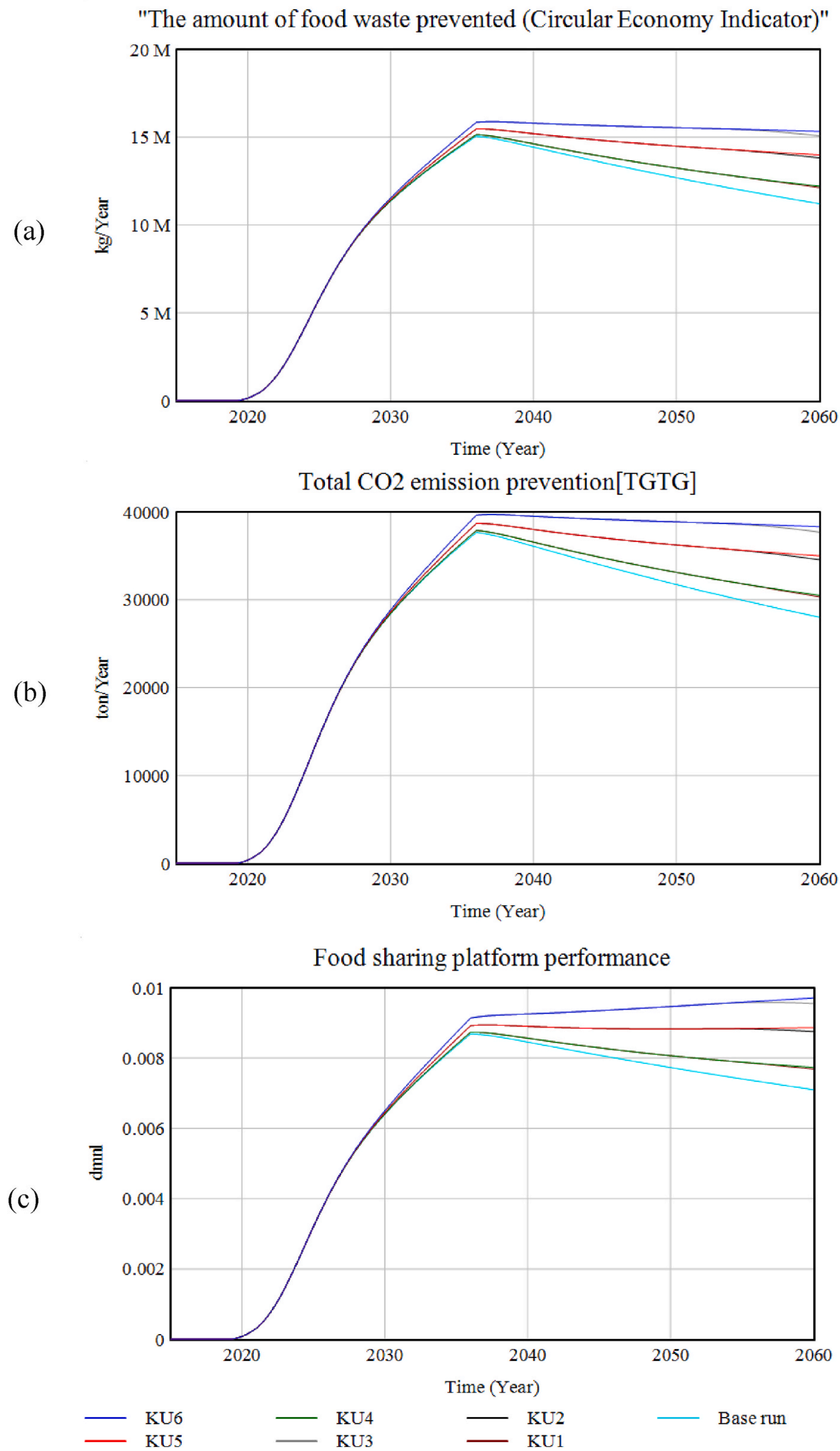

Fig. 16. The effect of knowledge enhancement among the under-aged population on the amount of FW prevented (the CE indicator) (a), the total CO_2 emission prevention (b), and TGTG performance (c).

frequently, by (i) highlighting the role users can play in saving the environment, and (ii), increasing their knowledge about the rationale behind the FSP and leveraging their awareness about food best time to use and expiration labeling, as already considered by the TGTG platform. Therefore, even if TGTG reaches its maximum potential user base, knowledge-enhancing programs can continue to enhance the app's appeal and encourage more frequent usage, resulting in greater prevention of FW. The key point is that while marketing forces the initial take-off of the number of users and gives it a sharp slope, knowledge-enhancing programs keep the attracted users in the system.

Fig. 17 presents a comparison between the estimated FSP performance in the year 2060, based on the discussed scenarios KA2, KA8, KA11, and KU6. As can be seen in this figure, the effect of knowledge enhancement among individuals younger than 18 on the TGTG platform performance in 2060 is far lower than scenarios related to improved knowledge-enhancing activities for adults. The main reason is the time lag that the under-aged population requires for maturing, which makes the knowledge enhancing efforts less effective in the near future. Furthermore, a comparison between the scenarios related to knowledge enhancement among adults shows that a significant difference exists between the result of scenario KA2 and the result of scenarios KA8 and KA11, which contain extra knowledge-enhancing efforts. This is while the outcome of implementing scenarios KA8 and KA11 on the TGTG platform performance in 2060 is very close to each other.

The maximum value for performance is 1; however, as the FW in supermarkets and shops that can be prevented constitutes a small fraction of the total amount of FW in Italy, very high performance cannot be expected for the TGTG platform. Nevertheless, the higher the performance of this platform in terms of FW prevention, the more favorable the app is.

Based on the analyzed scenarios, a potential general policy to improve the performance of TGTG FSP as much as possible could be to keep the current marketing efforts in place for 10 years and consider extensive knowledge-enhancing programs for all populations, both children and adults. This policy is tested in this section considering different scenarios, as reported in Table 6. High, average, and low knowledge enhancement effectiveness are set to 0.8, 0.5, and 0.2 in the model, respectively.

As can be seen in Fig. 18(a), scenario A results in the highest number of well-informed adults, followed by scenario B. In both scenarios, the knowledge-enhancing programs for adults are highly effective. However, scenario B has a lower effectiveness of knowledge-enhancing programs for the under-aged population compared to scenario A, leading to approximately 420,000 fewer well-informed adults in 2060. The number of well-informed adults in these scenarios is significantly higher than that of the base run, which is approximately 7.513 million. The same order of scenarios can be seen in Fig. 18(b), which illustrates the number of users. However, the number of app users in 2060 in scenarios A and B are estimated to be approximately 22.752 million and 22.703 million, respectively, which is significantly higher than the number of users in the base run (17.524 million). The number of users starts to decrease from the year 2047, which can be linked to the reduction of population in Italy. Hence, the recommended policy containing knowledge-enhancing programs for both adults and the under-aged population can be considered a winning policy in terms of the number of users, with a significantly higher number of future users in comparison with the base run.

In order to analyze the impacts of implementing this policy, the values of the key variables in 2060 are presented in Table 7. As can be seen in this table, all scenarios perform significantly better than the base run in terms of the average number of annual food bags saved by each user, total number of saved food bags, total amount of FW prevented, total CO_2 emission prevented, and the food sharing app performance. However, scenario A is also the best scenario in terms of environmental indicators.

Fig. 18(c) shows the dynamics in the TGTG platform performance in response to applying the analyzed scenarios, which can be considered the most crucial indicator to evaluate the contribution of TGTG FSP in transitioning towards the CE. As can be seen in this figure, by implementing each of the proposed scenarios, the performance of the TGTG FSP improves. Similar to the number of users, this indicator is higher if scenario A is prioritized to be implemented. The promising point in this figure is the increasing trend of platform performance that continues until the end of the simulation period.

To provide a clearer image of the potential role TGTG can play in preventing FW and transitioning towards the CE, Fig. 19 shows the share of FW prevented through the TGTG platform in 2060 from the total FW in Italy by implementing scenario A and also the base run. Based on this figure, the share of FW that can be prevented from the total FW in Italy in 2060 can reach approximately 3% by keeping the current effective marketing campaigns for 10 years, continuing the current training programs for supermarket staff and other people in the society by 2060, and at the same time, putting highly effective knowledge-enhancing programs both for adults and for under-aged population into force. Although scenario A has the best outcome among the analyzed scenarios, implementing any other scenario under the umbrella of the recommended policy, containing strong knowledge-enhancing programs for all the population, continuing the currently active knowledge-enhancing programs until 2060, and keeping the current strong social media and marketing activities in place for 10 years, can significantly increase the performance of TGTG FSP in preventing FW.

This can represent a significant contribution of a digital platform in transitioning towards the CE by preventing a huge amount of food products from being wasted. However, these activities require strong support from policymakers, regulators, and governments that have already been addressed in the TGTG's pact. Beyond direct regulation and support, policymakers should also emphasize promoting sustainable production and consumption practices more broadly. Educating society about sustainable consumption, part of which is linked with sharing platforms, and providing support in adopting these technologies can facilitate the transition towards sustainable development and tackling climate change by encouraging a shift in people's lifestyles.

7. Implications for research: future development avenues

From a practical and managerial viewpoint, the groundbreaking simulation model developed in this research is a significant milestone. It stands as the inaugural diffusion model tailored explicitly for digitally-

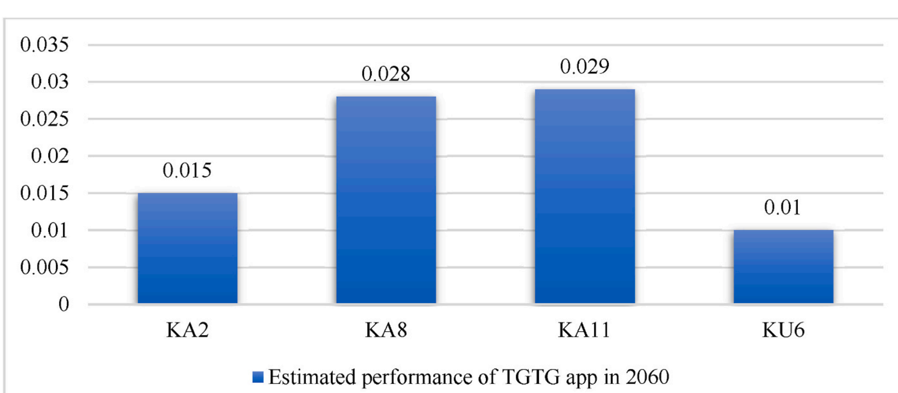

Fig. 17. The estimated performance of TGTG in Italy in 2060 in selected scenarios.

Table 6
Scenarios related to the recommended policy.

	Knowledge enhancement among adults				Knowledge enhancement among children		
	Currently active programs	Additional programs			Additional programs		
	Duration	Start	Duration	Effectiveness	Start	Duration	Effectiveness
Scenario A	Until 2060	2023	Until 2060	high	2023	Until 2060	high
Scenario B	Until 2060	2023	Until 2060	high	2023	Until 2060	average
Scenario C	Until 2060	2023	Until 2060	average	2023	Until 2060	average
Scenario D	Until 2060	2023	Until 2060	average	2023	Until 2060	high
Scenario E	Until 2060	2023	Until 2060	high	2023	Until 2060	low

enabled FSPs within the existing literature. Its versatility is a key asset, making it adaptable to a multitude of FSPs operating in various regions. This model holds immense potential for shaping the future of the food sector, particularly in its transition toward a CE model that aligns with sharing economy principles. For decision-makers and managers involved within the food supply chain, it can serve as a strategic tool for navigating the CE transformative journey. By harnessing the insights provided by this model, managers can strategize and implement initiatives aimed at three pivotal outcomes: (i) addressing critical environmental concerns associated with excessive FW, (ii) proactively reducing FW through prevention measures, and (iii) fostering resilient social communities while leveraging volunteer contributions to alleviate poverty and enhance food security.

However, incorporating the sharing economy concept into the food supply chain, as a potential solution towards a CE transition in the food sector, needs more investigations and further development. In this vein, after careful consideration based on the obtained results, four mainstreams of research were identified as potential research gaps and directions for future studies to better position the FW management agenda in line with the CE framework. The four research avenues identified herein call for: (i) exploring the rebound effects of FSPs, (ii) extending the presented model for FSPs, (iii) conducting empirical research to better frame food sharing initiatives and assessing their impact, and (iv) employing a mixed approach to simulation modeling, using SD and agent-based modeling for studying the impact of human behavior on the general dynamics of the system. The subsequent sub-sections provide a detailed exposition of the proposed agenda for advancing future research developments.

7.1. *Exploring the rebound effects of food sharing platforms*

Although CE as a solution to achieve sustainable development has gained much attention over recent years, CE initiatives often lead to rebound effects, which adversely impact their sustainability potential (Metic and Pigosso, 2022). For instance, in the case of digitally enabled FSPs, the rebound effects of food sharing for money business models are arguable. Such platforms have been initiated with the aim of reducing FW through promoting FW prevention in line with the CE principles. In contrast, many argue that although these platforms have provided an opportunity to prevent FW through distributing food surplus, the use of such applications can result in rebound effects, leading to emerging different lines of businesses for retailers to sell more food products (Meshulam et al., 2022; Yu et al., 2022). However, given the novelty of the urban FSPs, the contribution of the food sharing initiatives to the CE transition and a sustainable food supply chain is still blurred (Sarti et al., 2017), calling for further investigations. In this regard, as highlighted by Yu et al. (2022) and Meshulam et al. (2022), further research is required to investigate the potential rebound effects of FSPs to see whether the food sold on the platform is effectively a surplus or a planned production.

7.2. *Extending the presented model to address other unexplored aspects*

There are several points regarding the developed diffusion model for TGTG in the current research that can be addressed for further extension in future studies. In this vein, although the developed model has covered different dimensions of the FSP adoption, two factors have not been considered as deserved. First, the potential effect that well-informed adults may have on children, and the effect that well-informed children can have on their families to adopt the technology can create additional loops in the model. Considering this element in the developed model might add useful insight into the system and its behavior, however, it requires conducting surveys and gathering relevant data. Second, the effect of knowledge-enhancing activities on the attractiveness of adoption and effective usage of the TGTG app was considered linear. Hence, further developments can consider non-linear effects to compare the results.

Moreover, as the presented model is a general diffusion model for FSPs, it can be used to simulate the diffusion and impacts of other FSPs in other countries, proposing a promising direction for further research. However, unlike the presented reference case of TGTG in Italy, utilizing the present model for other countries with diverse food sharing apps might require the consideration of the spillover effect among the available apps. Furthermore, while the presented case addressed a food sharing for money platform, using the model for other food sharing business models may require additional assumptions or relevant data to distinguish between the diffusion of various existing business models.

Finally, considering the rapid pace of technological advancements, such as the emergence of artificial intelligence and Industry 5.0, it is crucial to explore their potential impact on market dynamics, user behavior, knowledge enhancement methods, and other relevant aspects. Understanding how these evolutions may influence the diffusion dynamics of FSPs entitles future investigation.

7.3. *Conducting empirical research to better frame sharing initiatives and assessing their impact*

The FSP domain and its implications and associated challenges lack sufficient empirical research and verifiable evidence. In this regard, more investigation is required to collect reliable data through various types of qualitative and quantitative methods, such as surveys and experimental analyses. In this regard, different players of FSPs, including potential consumers, businesses, retailers, and platform providers, should be considered and scrutinized. On the one hand, designing accurate and concrete surveys to evaluate the behavior, attitudes, and consumption patterns and habits of consumers should be addressed to better establish digitally enabled FSPs and food redistribution systems, especially in the case of peer-to-peer FSPs. On the other hand, collecting relevant data from for-profit and nonprofit organizations and businesses involved in any type of food sharing business model is of high importance to facilitate the adoption of such platforms in the future. Moreover, although some initial sustainability assessment tools have been proposed by several scholars, such as Mackenzie and Davies (2019) and Michelini et al. (2020), the literature in this area is still in its infancy stage. Therefore, designing sustainability assessment frameworks to evaluate the real impact of FSPs on the triple bottom line of sustainability, including social, environmental, and economic pillars, is strongly recommended for future research.

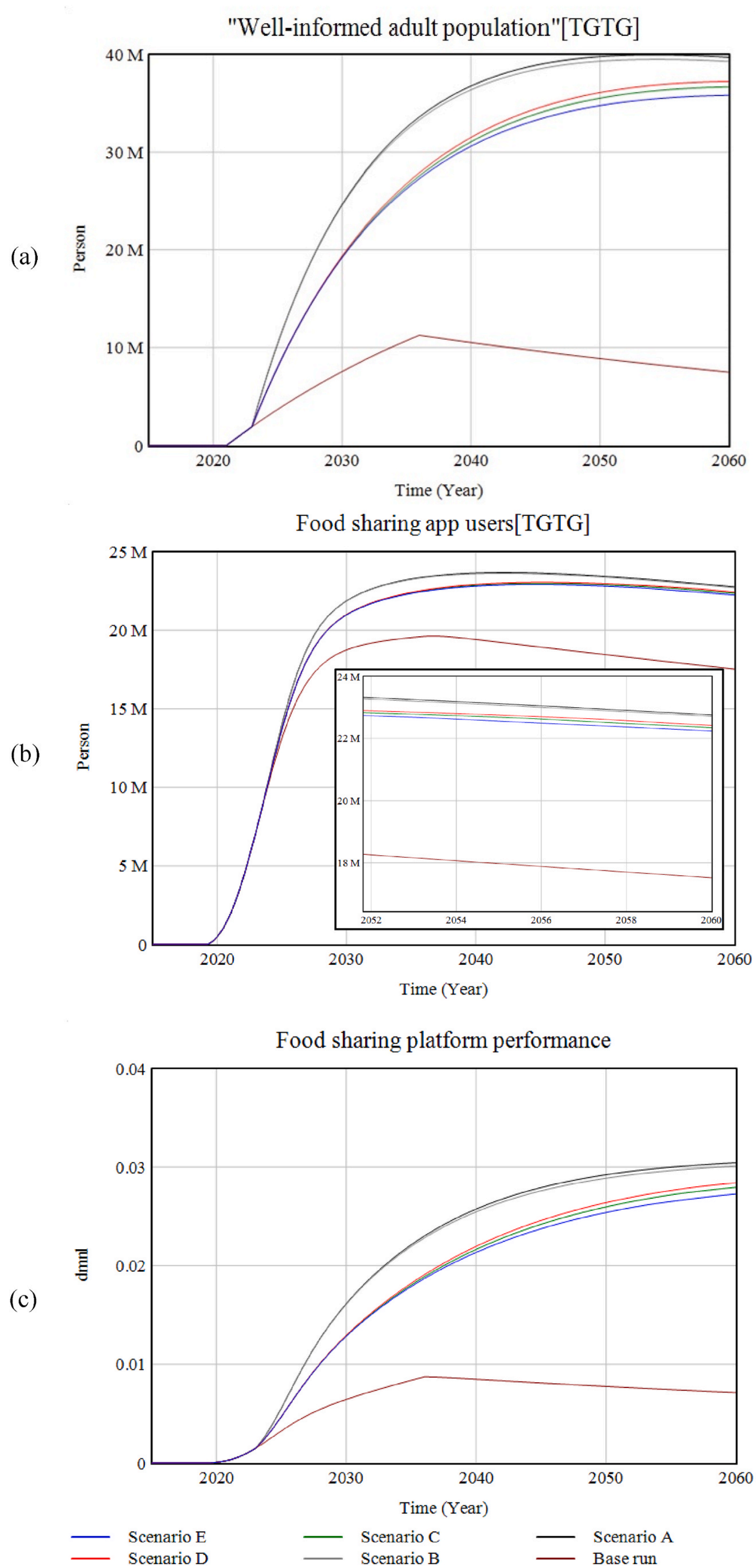

Fig. 18. The number of well-informed adults (a) and TGTG food sharing app users (b) in Italy by applying the recommended policy.

Table 7
Values of selected indicators in 2060 by applying various scenarios of the recommended policy.

Indicator	Base run	Scenario A	Scenario B	Scenario C	Scenario D	Scenario E
The average number of saved food bags per user per year	0.643	2.113	2.094	1.975	2.001	1.936
Total number of saved food bags	11.272 million	48.081 million	47.541 million	44.132 million	44.846 million	43.049 million
The amount of FW prevented (tons)	11,272.4	48,081.4	47,541.3	44,131.6	44,846.2	43049
Total CO_2 emission prevention (tons)	28,181	120,203	118,853	110,329	112,115	107622
FSP performance	0.0071	0.0305	0.0301	0.0279	0.0284	0.0273

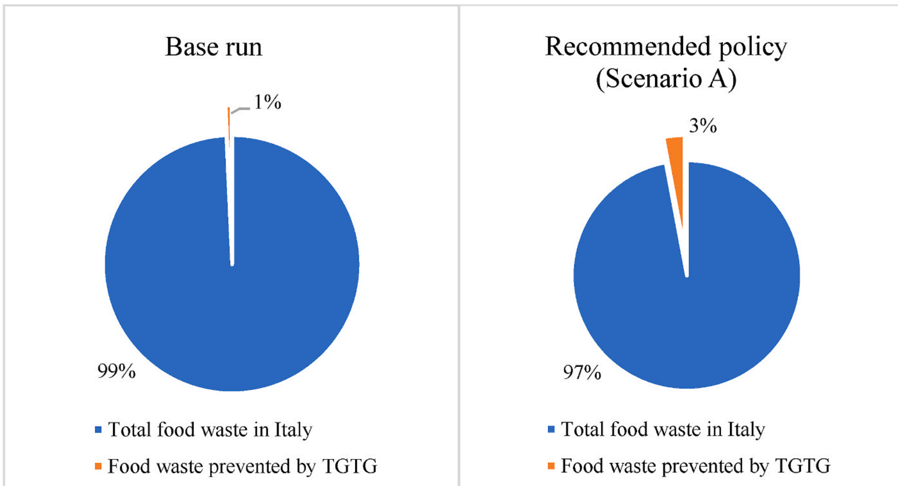

Fig. 19. The share of FW prevented by using the TGTG food sharing app from the total FW in Italy.

7.4. Employing a mixed approach to simulation modeling, using system dynamics and agent-based modeling

In this research, we have made clear the value of SD modeling for understanding the behavior of FSPs in terms of their adoption and performance in contributing to the FW prevention and CE transition. However, since each modeling approach can address different decision problems in any field of study, a combination of different modeling methods can potentially serve as a more useful approach in dealing with complex issues (Wei and Shang, 2023). Hence, a hybrid approach to incorporate other simulation models, such as agent-based models, into the developed SD model in the current research can provide a more detailed evaluation of the diffusion of FSPs. On this basis, complex interactions among different agents within the FSPs, including app users, points of sales (i.e., bars, restaurants, supermarkets, etc.), and authorities, can be effectively captured and modeled by agent-based models. Therefore, the results might advance the field and support research and developments in the FSPs arena towards implementing a CE in the food sector.

8. Conclusion

As one of the largest waste streams generated in the world, FW has brought severe implications for the global economy, the environment, and societies. Hence, sustainable initiatives to reduce FW by rethinking, redesigning, and operating all practices within the food supply chain are crucial in the transition towards a CE in the food sector. On this basis, alternative distribution channels in food supply chains using digital platforms, in particular, digitally enabled FSPs, have recently received attention as a solution to tackle the FW challenge at the consumption level. However, the contribution of the food sharing initiatives to a sustainable circular food supply chain is still unexplored and needs more research and development. Therefore, to shed light on the identified gap, an SD simulation model was developed in this research to specifically answer the following research questions: (i) how will the diffusion of digitally enabled FSPs evolve in the future; and (ii) to what extent can digitally enabled FSPs help FW prevention in a CE? Then, through testing various scenarios, the effect of different levels of knowledge-enhancing activities and marketing plans on the adoption and performance of such platforms over time was analyzed and discussed. In this regard, the TGTG platform in Italy, as a well-known food sharing for money app, was studied as a reference case.

The simulation results show that TGTG is a successful FSP in terms of adoption by users in Italy. However, the performance of this platform regarding its potential to reduce FW can still improve to a large extent. In this regard, the findings denoted that the current marketing strategy of TGTG is performing effectively, hence, keeping the current marketing campaign for around 10 years will sustain the market share of TGTG. Nevertheless, the knowledge-enhancing portfolio of TGTG needs more developments and improvements to increase TGTG's performance by enabling more effective usage of the app and, accordingly, more FW prevention. More particularly, (i) the number of users can still grow up using more effective and longer-run knowledge-enhancing plans and programs by increasing the public's knowledge regarding the FW crisis and its adverse implications for the environment, resource efficiency, food security, and hunger, and (ii) even if the number of TGTG users reaches the maximum potential number, knowledge-enhancing programs can still work towards increasing the attractiveness of more frequent usage of the app and save a higher amount of food products from being wasted. Hence, putting knowledge-enhancing activities at the core, a proper policy for TGTG was recommended, which can lead to a reduction of approximately 3% in the total FW generated at the country level (Italy) in 2060.

The simulation model developed in this research is the first diffusion model developed for digitally enabled FSPs in literature and is a general model, which can be used for any number of FSPs in any region. Hence, it can significantly contribute to the CE transition in the food sector by embracing the sharing economy concept, and it can guide food supply chain stakeholders and policymakers in incorporating sharing economy in the food sector to (i) reduce FW through FW prevention, (ii) tackle environmental concerns related to the huge amount of FW, and (iii) create strong social communities and use volunteer potential to help food security and poverty alleviation towards achieving Sustainable Development Goals 2 (zero hunger) and 12 (responsible consumption and production).

Nevertheless, the presented case for the TGTG FSP faced two main limitations, first, lack of accurate data, and second, not considering the effects of the COVID-19 pandemic. The lack of accurate data regarding the activities of sharing economy platforms is mainly because these service providers do not provide access for the public to their database. Using more accurate data would result in achieving results closer to reality. Moreover, it is obvious that the pandemic has affected the application of food-related industries and businesses worldwide (Ranjbari et al., 2021b). However, due to the lack of any reliable research on the case of TGTG and COVID-19 implications, the effect of the pandemic outbreak on the level of diffusion of TGTG was not considered. Hence, in case of data availability, incorporating the pandemic effects into the model might provide some insights and more accurate results in future developments.

Data availability

Data will be made available on request.

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