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Modélisation de la diffusion de l'innovation dans les réseaux sociaux

Présentée par : Rima Benfredj

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Department of Computer Science

THESIS

In order to obtain the Doctorate degree in LMD (3rd cycle)
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THEME

Modeling the diffusion of innovation in social networks

By: Rima Benfredj

Publicly defended on: 28 / 01 /2026.

In front of the jury composed of:

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2025-2026

Dedication

Alhamdulillah, the entire praise is due Allah for giving me the strength, patience, and guidance I needed to finish my voyage.

I dedicate this dissertation to my beloved family, with special thanks to my wonderful father, whose unfailing support and encouragement have been a great source of strength, and to my loving mother, whose care and prayers have been with me at all times. My greatest appreciation extends to my brother, sisters, and their families for all they do for me.

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Rima Benfredj, 2026

Abstract

Modeling the diffusion of innovation in social network

Recently, the diffusion of innovation has seen a paradigm shift and emerged as a renewed and interesting field due to advances in artificial intelligence, behavioral modeling, and empirical simulation. Understanding adoption behavior is increasingly complex, as individuals' decisions are influenced not only by innovation attributes and social pressure but also by psychological characteristics, especially personality traits. This thesis offers a personality-driven diffusion model that integrates Big Five personality framework (OCEAN) into the Rogers' Diffusion of Innovation theory. Using agent-based modeling (ABM), individuals are presented as agents having distinct profiles, which shapes their perception of innovation features (relative_advantage, compatibility, complexity, trialability, observability). The framework consists of four major phases: perception, communication, persuasion, and decision. The special feature of the present research is the two-phase modeling strategy: (1) an exploratory simulation with randomly generated values in order to understand the fundamental diffusion dynamics. (2) the model is applied empirically, by applying a hybrid BERT-Random Forest model to predict Twitter users' personality traits based on ChatGPT-related data, these extracted qualities are subsequently used to regenerate the values of the remaining model' attributes and simulate adoption processes. The findings demonstrate that actually adoption behavior is profoundly influenced by personality-driven dimensions, resulting in more realistic adoption curves than traditional models. This approach opens up new perspectives for the behavioral study of innovation diffusion.

Keywords: Diffusion Of Innovation theory (Rogers), Personality traits, Big Five model (OCEAN), Agent-based modeling, ChatGPT-related tweets, Machine learning, Deep learning, BERT, Random Forest, Social Network Analysis.

Résumé

Modélisation de la diffusion de l'innovation dans les réseaux sociaux

Récemment, la diffusion de l'innovation a connu un changement de paradigme et est devenue un domaine d'étude renouvelé et passionnant grâce aux progrès de l'intelligence artificielle, de la modélisation comportementale et de la simulation empirique. Comprendre le comportement d'adoption est devenu plus complexe, car les décisions individuelles sont influencées non seulement par les caractéristiques de l'innovation et la pression sociale, mais aussi par des caractéristiques psychologiques, notamment les traits de personnalité. Cette thèse propose un modèle de diffusion axé sur la personnalité, intégrant le cadre de personnalité Big Five (OCEAN) dans la théorie de la diffusion de l'innovation de Rogers. Basée sur la modélisation multi-agents (ABM), les individus sont présentés comme des agents ayant des profils distincts, qui influencent leur perception des caractéristiques de l'innovation (avantage relatif, compatibilité, complexité, possibilité de test, observabilité). Le cadre comporte quatre phases: perception, communication, persuasion, et décision. La particularité de cette recherche réside dans sa stratégie de modélisation en deux phases : (1) une simulation exploratoire avec des valeurs générées aléatoirement afin de comprendre la dynamique de diffusion fondamentale. (2) le modèle est appliqué empiriquement, en utilisant un modèle hybride BERT-Random Forest pour prédire les traits de personnalité des utilisateurs de Twitter à partir des données liées à ChatGPT. Ces qualités extraites sont ensuite utilisées pour régénérer les valeurs des attributs restants du modèle et simuler les processus d'adoption. Les résultats démontrent que le comportement d'adoption est profondément influencé par des dimensions liées à la personnalité, produisant des courbes de diffusion plus réalistes que celles des modèles traditionnels. Cette approche ouvre de nouvelles perspectives pour l'étude comportementale de la diffusion de l'innovation.

Mots-clés : Théorie de la diffusion de l'innovation (Rogers), Traits de Personnalité, modèle des Big Five (OCEAN), Modélisation basée-agents, Tweets liés à ChatGPT, Apprentissage automatique, Apprentissage profond, BERT, Random Forest, Analyse des réseaux sociaux.

ملخص

نمذجة انتشار الابتكار في الشبكات الاجتماعية

شهد انتشار الابتكار مؤخرًا نقلة نوعية، وبرز كمجال متجدد ومثير للاهتمام بفضل التطورات في الذكاء الاصطناعي والنمذجة السلوكية والمحاكاة التجريبية. ويزداد فهم سلوك التبني تعقيدًا، إذ لا تتأثر قرارات الأفراد بخصائص الابتكار والضغوط الاجتماعية فحسب، بل أيضًا بالخصائص النفسية، وخاصةً سمات الشخصية. تقدم هذه الأطروحة نموذجًا جديدًا للانتشار قائمًا على الشخصية، يدمج إطار العوامل الخمس الكبرى للشخصية (OCEAN) في نظرية روجرز لانتشار الابتكار. باستخدام المحاكاة القائمة على الوكلاء يُقدَّم الأفراد كوكلاء ذوي سمات مميزة، مما يُشكِّل تصورهم لخصائص الابتكار (الميزة النسبية، والتوافق، والتعقيد، وقابلية التجربة، وقابلية الملاحظة). يتضمن الإطار أربع مراحل: الإدراك، والتواصل، والإقناع، واتخاذ القرار. الميزة المميزة لهذا البحث تكمن في استراتيجية النمذجة المكونة من مرحلتين: (1) محاكاة استكشافية بقيم تم إنشاؤها عشوائيًا لفهم ديناميكيات الانتشار الأساسية؛ (2) يتم تطبيق النموذج تجريبيًا، باستخدام نموذج BERT-Random Forest الهجين للتنبؤ بسمات شخصية مستخدمي Twitter بناءً على بيانات ChatGPT.. تُستخدم هذه الصفات المُستخرجة لاحقًا لإعادة توليد قيم سمات النموذج المتبقية ومحاكاة عمليات التبني. تُظهر النتائج أن سلوك التبني يتأثر بشدة بأبعاد شخصية ، مما ينتج عنه منحنيات تبني أكثر واقعية من النماذج التقليدية. يفتح هذا النهج آفاقًا جديدة للدراسة السلوكية لانتشار الابتكار.

الكلمات المفتاحية :نظرية انتشار الابتكار (روجرز)، سمات الشخصية، نموذج العوامل الخمسة الكبرى OCEAN ، النمذجة القائمة على الوكلاء، تغريدات متعلقة بـ ChatGPT، التعلم الآلي، التعلم العميق، BERT، Random Forest، تحليل الشبكات الاجتماعية.

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General

Introduction

1. Context

In recent decades, innovation has emerged as one of the most significant drivers of economic growth, social evolution, and technological progress that improves quality of life and addresses social challenges. Innovation can be idea, service, model, product, technology, or anything that is perceived by the potential adopter as new. Diffusion, on the other hand, refers to the gradual spread of an innovation via a social system over time. The rapid growth of digital technologies, combined with the rise of artificial intelligence, has accelerated both the development and dissemination of innovation. Understanding how it diffuse throughout society has become increasingly essential. Therefore, recognizing the mechanisms and conditions that influence the global process of diffusion enables policymakers, businesses, decision-makers, as well as societies to better capitalize on the potential of new ideas to foster economic integration, competitiveness, and promote societal progress [1].

Innovation and its diffusion are complex processes affected by a variety of factors. Referring to literature, numerous theories and models have been proposed to investigate and determine these elements. However, the most significant theoretical advancement came with Everett Rogers' Diffusion Of Innovations (DOI) theory (1962), which provides a critical framework for understanding how new ideas, products, and technology get embraced and disseminated throughout society over time. According to this framework, the diffusion of innovation is ‘‘ the process by which an innovation is communicated over time among the members of a social system through particular channels’’[2], it indicates that the rate of adoption and diffusion is influenced by four main factors, including innovation with its five characteristics, communication channels used to promote it, the time dimension, and the social system in which the innovation is diffused. As a result, the theory describes the well-known S-shaped adoption curve and classifies adopter into innovators, early adopters, early majority, late majority, and laggards.

While the essential ideas of this theory continue to be relevant, the diffusion of innovation theory and subsequent diffusion models typically oversimplify the diffusion process by overlooking the complex nature of human decision-making and psychological dimensions influencing adoption behaviors. However, current researches emphasize the necessity of understanding not only structural elements like communication channels, or social networks, but also individual-level determinants that influence how individuals perceive and adopt innovations.

Large field experiments and studies frequently show non-significant impacts for innovation's five dimensions, indicating that these features are not consistently robust across settings [3], [4], [5]. A potential reason for this inconsistency is a lack of dynamic measurement in existing models; many depend on static perceptions of these attributes at the point of adoption, ignoring the fact that perceived innovation attributes can evolve during diffusion process, with psychological dimensions can have a significant impact on this evolution.

Furthermore, heterogeneity of the targeted population occurred in a simple manner due to considerable variations in perceived innovation features. However, in real diffusion modeling, it is critical to recognize that heterogeneity stems from the diversity of communication and interaction behaviors, in perception phase and personal evaluation of perceived innovation attributes, in decision-making process, as well as the variety of values present within individual-level characteristics. Collectively, these limitations highlight the need for a novel diffusion model that account for psychological factors in individual-level differences**.**

Among these psychological elements, personality traits are especially important. Recent academic research highlights an increasing interest in understanding this individual-psychological factor that drive innovation adoption [6]. Particularly, the Big Five model (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) has shown that personality influences how human behave, communicate in social network, and make decisions. Individuals with high openness, for example, are more likely to accept innovation and be willing to adopt novel technology, whereas those with high neuroticism may be resistant due to increased level of uncertainty and decreased interpersonal interactions. By aggregating such variations among the population, personality traits influence not just individual decision-making but also the overall diffusion process.

Studies notably [7], [8], and [9] examined how openness to experience and neuroticism traits influence the adoption of e-learning environments, mobile banking, and e-technologies. Additionally, others have studied the concept of personal innovation, which is a reflection of an individual's extraversion [10], risk-taking traits, openness to new experiences, and willingness to experiment with new technologies [11], [12]. Research on the adoption of cryptocurrencies [13] and blockchain technology [11] has also shown that these characteristics are important for the adoption of innovations.

Although these studies have looked into the role of individual traits in innovation adoption, such as openness, extraversion, and neuroticism, they are typically limited to specific technologies (e.g., e-learning, mobile banking), may be inapplicable in other contexts, and fail to provide a generalizable framework. Critically, these research studies usually examine personality in isolation, focusing primarily on individual-level traits while ignoring other important aspects of diffusion theory such as innovation characteristics, communication dynamics, peer effect, and the different innovation-decision stages. This fragmentation highlights the need for a more comprehensive, personality-driven diffusion model that combines psychological diversity with the core aspects of innovation diffusion theory.

2. Contributions

The present thesis contributes to the literature by combining Rogers' innovation diffusion theory, psychological insights, and computational modeling into single framework. The primary contributions are as follows:

1. **Theoretical contribution**

- Developing a personality-driven diffusion model that combines the DOI framework with the OCEAN personality characteristics.
- Explicitly examines the effect of individual psychological traits on adoption decisions, perceptions of innovation features, individual’ persuasion level based on peer influence, and social interactions.

2. **Methodological contribution**

- Agent-Based Simulation (ABS) is used to represent heterogeneous agents, each having its own personality traits and perceived innovation features. ABS simulate individual interactions, directed by personality-driven decision-making, resulting in global diffusion patterns that align with the standard S-shaped curve.
- Two-phase simulation approaches

- ✓ Random initialization for personality traits, innovation and perceived innovation values to explore basics dynamics.
- ✓ Real-world experiment: a hybrid BERT-Random Forest model predicts Big Five personality traits from ChatGPT-related data, which are then utilized for regenerating the remaining qualities of the model for simulation.

3. Practical/Application contribution

The case study focuses on the adoption of ChatGPT, which is an exceptional instance of rapid technology adoption in digital society. By analyzing its dissemination, the thesis demonstrates how personality-driven modeling depicts realistic diffusion patterns and individual adoption behaviors.

This thesis presents a comprehensive, personality-driven diffusion model that incorporates DOI theory, individual psychological factors, innovation characteristics, and social network characteristics. It provides a solid framework to understand and model the diffusion of innovation at the individual and network levels by combining theoretical rigor with empirical grounding.

3. Thesis outline

The present thesis has been organized within three primary chapters, in addition to the general introduction and conclusion. The subsequent chapters are structured as follows:

1. **Chapter 1: Background**- This chapter provides an in-depth literature review of the fundamental concepts of this research, beginning with the diffusion of innovation theory in the first section, progressing to the agent-based modeling approach, and ending with personality theory and models later.
2. **Chapter 2: Proposed model: A personality-driven innovation diffusion model** - In this chapter, we present a thorough description of the suggested personality-driven innovation diffusion model, therefore we divide it into two useful sections. We constantly present the theoretical basis of our suggested model in the first part. Section 2 describes how the model is implemented using agent-based simulation with random initialization.
3. **Chapter 3: Use of the proposed model with automatic personality traits prediction for ChatGPT adoption-** The third chapter is a practical application of the personality-driven innovation diffusion model, with the goal of testing and validating the model's robustness. The chapter provides a critical overview of the automatic personality trait prediction field,

including recent researches and models used to forecast it. Then, in the second section, we outline, demonstrate, and justify the selection of the BERT-RF prediction model as well as the reuse of real extracted user personality traits to regenerate values for the other model variables. As a case study, we examine the adoption of ChatGPT on the Twitter network.

Chapter 1.

Background

1.1. Introduction

Human life is marked by its dynamics and constantly evolving nature. We possess an inherent inclination to seek out fresh opportunities, experiences, and knowledge. Our capacity to venture into the unknown, adapt to change, and uncover novel aspects propels our personal growth and contributes to the advancement of society. Moreover, humans have been motivated by a thirst for knowledge, and as a curious being, they have always been attracted to novel discoveries and new experiences, whether it's knowledge, technology, art or even human connections.

Throughout history, innovation has fundamentally affected the course of human life, and served as the driving force behind our progress. The adoption of innovation is not a choice but a requirement for human existence and growth. It enables us to overcome obstacles, improve our quality of life, and gain a better understanding of the universe. However, a variety of factors heavily influence the rate and scope of innovation adoption.

Diffusion **O**f **I**nnovations (DOI) theory, a sociological theory developed by Everett Rogers in the 1960s, also outlines several factors that influence the speed and extent of diffusion. It helps identify critical elements influencing diffusion and develop strategies to enhance the adoption and effective implementation of innovations.

This chapter divided into two parts. The first one aims to provide and discuss the diffusion theory, showing its' definition, its key elements, and a lively summary on the diffusions' models. To correctly position our contribution, we provide an overview of agent-based modeling, presenting the key elements of this approach. Besides, in the following part we give an in-depth state of the art regarding personality, personality traits, and provide a summary on existing personality models. Finally, we conclude this fruitful discussion with a chapter' conclusion.

1.2. Diffusion Of Innovation theory (DOI)

≪ A slow advance in the beginning, followed by rapid and uniformly accelerated progress, followed again by progress that continues to slacken— until it finally stops: These are the three ages of . . . invention . . . . If taken as a guide by the statistician and by the sociologist, [they] would save many illusions ≫

Gabriel Tarde (1903, p. 127), The Laws of Imitation.

According to [2]' definition, the diffusion of innovation is ‘‘the process by which an innovation is communicated over time among the members of a social system through particular channels’’. In this context, [14, p.489] defined the diffusion term as ‘‘the process through which an innovation (an idea, product, technology, process, or service) spreads (more or less rapidly, in more or less the same form) through mass and digital media, and interpersonal and network communication, over time, through a social system, with a wide variety of consequences (positive and negative)’’.

Diffusion of innovations theory, in my own words, is a theoretical framework created by Everett Rogers in 1962 that offers a conceptual foundation for comprehending how novel ideas, new technologies, or new products spread within a particular community. It helps to clarify the various stages that an innovation goes through, the different types of adopters involved, and the different factors that affect the diffusion process.

In the context of the theory of innovations diffusion, the term diffusion refers to the process of spreading a new innovation within a given population. This process entails the transmission of information, ideas and experiences relevant to innovation, promoting its adoption and implementation by new potential users. The theory, according to [2], is founded on several key principles including:

1.2.1. The innovation

The key notion of the theory, which can be defined as a new idea, technology, practice, service, or product that is seen as novel or superior to what previously existed.

It is crucial to note that innovation is defined by a collection of characteristics known as perceived attributes of innovation, which play a key role in the process of innovation adoption and diffusion. Here is a full explanation of the primary innovation characteristics:

1.2.1.1. Compatibility

Compatibility refers to the fit of the innovation with the values, needs and pre-existing experiences of members of the social group. The more an innovation is perceived as compatible, the more likely it is to be adopted, because it is perceived as consistent with existing norms and with group objectives. However, an incompatible innovation, it may take a long time and a lot of discussion before it becomes socially acceptable [15].

1.2.1.2. Relative_advantage

Relative_advantage is the perception that individuals have regarding the superiority of innovation in relation to existing alternatives. If an innovation is perceived as offering significant advantages, such as greater efficiency, better quality or cost savings, it will be more attractive for adoption. This factor is considered a prerequisite for adoption [16], and the higher the perceived relative_advantage, the faster the adoption process is likely to occur [2].

1.2.1.3. Complexity

Complexity referring to the degree to which an innovation is perceived as difficult to understand and use [17]. The more complex an innovation, the more difficult it is for individuals to adopt it. Simple and easy to understand innovations tend to be adopted more quickly. In other words, simplicity plays a crucial role in the adoption process, and innovations that are perceived as simpler are more likely to be quickly adopted [2]. However, complexity can be overcome if training and support resources are available to help potential adopters to master innovation.

1.2.1.4. Trialability

Trialability relates to the ability of potential adopters to experiment or test an innovation before fully adopting it, or having the ability of trying partially with the objective to eliminating ambiguity. When individuals can try an innovation in a limited way and assess its benefits for themselves, perceived risk is reduced and adoption is facilitated. The more times an innovation is tried, the more quickly it is adopted [15], [17].

1.2.1.5. Observability

Observability considers the visibility of the innovation and its results. When individual can observes the tangible benefits of the innovation in other people or organizations, he will be compelled to talk about it and will frequently request assessment information. As a result, it can boost his confidence and encourage him to adopt it. For example, if a new product clearly improves the performance of a competitor's business, it may motivate other businesses to do the same. To summarize, observability can accelerate the diffusion process if the adoption and its related benefits are readily observable [15].

These five attributes; relative_advantage, complexity, compatibility, observability, and trialability; are widely recognized in the literature as key characteristics of innovation, as presented by Everett Rogers in his theory of the diffusion of innovation.

The literature has also provided other characteristics that can influence the adoption of innovation. For instance, [18] specified five more characteristics of an innovation. These include cost, divisibility and communicability, social approval, and profitability. They are thought that communicability is synonymous with observability, and that divisibility is related to trialability. Price and profitability are not necessarily important factors in the acceptance of an innovation, and social approval is somewhat dependent on the previously described traits.

Additionally, other works have expanded on Roger's work, proposing new variables for the model; image is defined as the extent to which the adoption and use of the innovation is regarded to improve one's image or standing. Trust is defined as the degree to which the innovation adopter believes the innovation supplier is trustworthy[19].

Beyond the core characteristics, voluntariness is defined as the degree to which adoption is regarded to be free or spontaneous. It is vital to assess whether individuals are free when examining the diffusion process. The degree of voluntariness is classified as a specific type of decision by diffusion theory [20].

Davis [21], highlighted that acceptance is determined by two concepts: usefulness and ease of use. Usefulness is a subjective evaluation metric that assesses whether an innovation is appropriate and valuable. The degree of lack of physical and mental effort required to use the innovation is indicated by its ease of use.

For Rogers, the risk is not a separate term; it is included in the relative_advantage. Separating and taking into account a single characteristic independently of the others is not advisable to predict the future of innovation [20]. In this regard, researches have indicated that possessing more positive characteristics increases the chances of adoption.

1.2.2. Communication

Communication is ‘‘the process in which participants create and share information with one another in order to reach a mutual understanding’’ [2, p.5]. Communication is critical in the adoption and diffusion of innovations process. It allows the information transmission about the innovation, its qualities, benefits, and applications to members of a social system. Communication can be viewed as a technique of persuading, influencing, and convincing future adopters of the worth and interest of innovation. It can take place via several channels, which are the means used to transmit information.

1.2.2.1. Communication channels

In Rogers' classical formulation of diffusion theory, communication channels were categorized into two primary forms:

- **Interpersonal communication channels**. Occurs when people exchange information directly with one another. This can be accomplished through face-to-face chats, phone calls, meetings, and so on. Interpersonal communication is frequently seen as a successful route for disseminating innovations because it provides for direct connection, the ability to answer inquiries, explain doubts, and provide tailored support.
- **Mass media.** Such as television, radio, newspapers, magazines are large scale communication

channels. They contribute significantly to the diffusion of innovations. They make it possible for information to reach a large audience in a fast and effective manner. Mass media has the ability to influence public opinion, spark interest in innovation and inform potential adopters of its features, benefits and availability. Media reports and advertising campaigns are two examples of mass media-based communication methods.

These two types of communication play an important role in the process of diffusion, as an integral part. Over time, with the advent of the internet, social media platforms, and interactive digital environments, new hybrid channels have been introduced to speed up and open up the opportunities for the diffusion of innovations. They enable rapid dissemination, direct engagement, and peer-to-peer influence at scale, thereby complementing and, in some cases, reshaping the traditional communication channels.

Moreover, it is especially important to note that the effectiveness of communication channels varies based on the context and target audience. Some channels may be more suited to disseminating innovations to specific communities, while others may be better suited to reaching wider audiences. Innovators need to comprehend the characteristics and preferences of their target audience in order to select the most relevant communication channels for efficiently disseminating their innovations.

Uncertainty. Novelty imposes a certain degree of uncertainty, which is implied by the absence of complete information. One of the most important ways to eliminate uncertainty is through communication.

1.2.3. Time

≪ New ideas pass through three periods: 1) It can't be done. 2) It probably can be done, but it's not worth doing. 3) I knew it was a good idea all along! ≫ Arthur C. Clarke

The success of innovation diffusion is typically measured in terms of time [22]. As thus, the time dimension is a key factor of the innovation diffusion theory, because whatever the innovation contribution is, it spreads slowly throughout the population. As a result, it takes time from its availability to its diffusion [20], [23]. Furthermore, time emphasizes that the adoption of an innovation is not a one-time event; rather, it occurs over time and follows a unique adoption curve. Typically, the adoption curve depicts the cumulative percentage of the target population that adopts the innovation at various periods in time.

1.2.3.1. The decision-making process

The decision to accept, adopt, and use the innovation does not have to be made immediately, rather, it does take time. [16] describes the adoption decision as a five-phase decision-making process that begins with initial exposure to an innovation until its adoption or rejection as shown in (Figure 1).

1.2.4. Social system

In diffusion theory, the social system is defined as, ‘‘a set of interrelated units that are engaged in joint problem solving to achieve a common goal … individuals, informal groups, organizations, and/or subsystems’’. This is a broad umbrella concept that encompasses social structures, social consequences, system norms, opinion leaders and change agents, and innovation adoption decisions [24].

The social structure can significantly influence the diffusion of innovation, as well as the nature of interpersonal relationships, which can influence the impact of knowledge and experience exchange. For example, while different communication channels might influence how knowledge flows through an organization, the structure of the social system can also limit an innovation's ability to scale beyond the point of disuse [22]. So, knowledge of social structures is vital for the diffusion of innovation because it puts adopters at the heart of the diffusion's success [20].

1.2.4.1. Opinion leaders

Are those who, by their social accessibility, conformance to system norms, and technical expertise, able to influence the opinions, attitudes, motives, and behaviors of others in the social system, either formally or informally [24]. Opinion leaders' behavior is important in determining the rate of adoption of an innovation in social system; in fact, the diffusion curve has its typical S-shaped form due to the time at which the opinion leaders adopt and their ability to activate diffusion networks in social system [25].

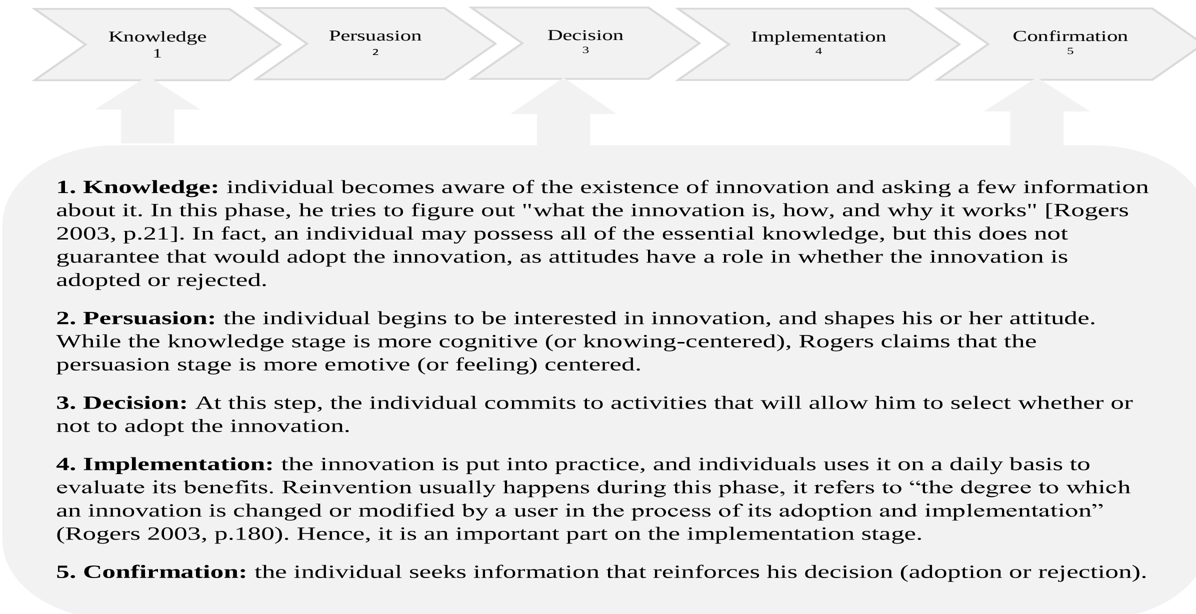


Figure 1. The Decision-making process.

1.2.4.2. Change agents

Change agents are persons who can influence innovation decisions but, unlike opinion leaders, are professionals with competence in specific domains and have social status associated with them. Both opinion leaders and change agents frequently affect social norms, change behaviors and can serve as intervention intermediaries. In literature, they have been identified as significant drivers of innovation diffusion [24].

1.2.4.3. Social pressure

This term often used to express the influence of the social network. It refers to the extent to which an individual may feel under pressure to adopt an innovation because of other people's opinions or because of social pressure [20].

Voluntarism is the readiness of individuals to accept without external pressure. The extent of one's own volition while making a choice distinguishes individualism from collectivism. The opposite end of the social pressure spectrum is voluntarism.

1.2.4.4. Social contagion

According to the social contagion hypothesis, simply contact with an infected person is typically enough to transmit the behavior or information. This is similar to how disease spreads. People close in social structure to whom that individual returns to handle uncertainty typically causes social contagion [20].

1.2.5. Innovation diffusion cycle

In a social system, not all individuals adopt an innovation at the same time. Rather, individuals adopt it in a chronological sequence, and they can be categorized as adopters based on when they first start using the innovation [16]. Rogers within this edition (1962) presents a detailed theory of how innovations spread through populations and how different individuals respond to the adoption of new ideas, products or technologies.

One of Rogers' most significant contributions is the categorization of individuals into different groups based on their readiness to adopt an innovation. This categorization represented graphically as a bell curve (Figure 2), which is generally divided into five segments. Each category reflects the amount of time it takes for an individual to adopt a particular innovation relative to the average adopter.

1.2.5.1. Innovators

According to Rogers' classification system, ‘‘Innovators’’ comprise only 2.5% of adopters. These individuals possess a strong ambition towards new ideas, are highly venturesome, and often aim to lead the way in embracing change. They are the first to adopt new innovations and take calculated risks to do so.

1.2.5.2 Early adopters

In contrast, ‘‘Early adopters’’ represent 13.5% of adopters and closely follow the innovators. They are respected role models in their peer networks, often viewed as opinion leaders, and are consulted by colleagues prior to implementing new ideas. While they are also willing to try new things, they approach innovation with greater caution than innovators.

1.2.5.3. Early majority

Moving on to the third category of adopters, the ‘‘Early majority’’ accounts for 34% of adopters. While they are less likely than the previous categories to hold positions of leadership, they are thoughtful and pragmatic, seeking out developments that improve their lives rather than making changes for their own sake. They are also more adaptable to change than the remaining categories of adopters. Due to their abundance and persuasibility, businesses often target this group as their preferred market.

1.2.5.4. Late majority

The ‘‘Late majority’’ also comprises 34% of adopters and tends to react to innovations later than their peers. They are hesitant to adopt new ideas and prefer to wait until any uncertainty surrounding an innovation has been resolved before embracing it. They are also more likely to adopt an innovation only after it has been widely accepted by others in their social network.

1.2.5.5. Laggards

The final category of adopters, comprising 16% of the total, is the ‘‘Laggards’’. These individuals are typically more traditional and less trusting of innovations and change agents than the late majority. They lack leadership roles and tend to make decisions based on whether an innovation has already been successfully adopted by other members of their social system. As a result, their innovation-decision period is relatively long compared to the other categories of adopters.

1.2.6. Types of innovation-decision

According to [16, p.29], individual members of a system can adopt or reject an innovation, or the entire social system can decide to adopt an innovation by a collective or authority decision.

1.2.6.1. Optional innovation-decisions

Optional decisions are decisions to adopt or reject an innovation made by an individual, independent of the decisions of other system members. Even in this scenario, the individual's decision may be influenced by his system's norms as well as his interpersonal networks. The distinctive feature of optional innovation-decisions is that the individual, rather than the social system, is the unit of decision-making [16, p.29].

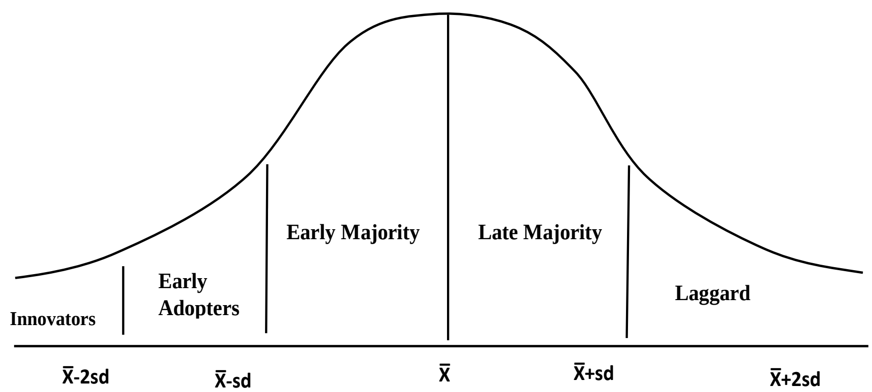


Figure 2. The bell-shaped frequency curve (Adopter categorization). Rogers 2003

Rogers mentioned in [16] that numerous characteristics are used to classify adopters. The sample's mean (x), or average, is one of these characteristics or parameters. The standard deviation (sd), a measure of dispersion around the mean, is another distribution parameter. The standard deviation of a sample explains the average amount of variance on either side of the mean. The mean (x) and standard deviation (sd) statistics can be used to partition a normal adopter distribution into categories. When vertical lines are created to denote the standard deviations on either side of the mean, the curve is divided into categories, yielding a standardized percentage of respondents in each.

1.2.6.2. Collective innovation-decisions

Collective innovation-decisions are decisions to embrace or reject an innovation determined by consensus among system members. Once a decision is made by the system, all of the units in the system must usually conform to it [16]

1.2.6.3. Authority innovation-decisions

Authority innovation-decisions are decisions to adopt or reject an innovation made by a small group of individuals in a system who have power, prestige, or technical expertise. The individual system member has little or no impact on the innovation decision; he merely implements it [16, p.30].

These three previously discussed types of innovation-decisions range from optional decisions, where the adopting individual bears almost full responsibility for the decision, through collective decisions, where the individual has some influence in the decision, to authority decisions, where the adopting individual bears no influence in the decision. In formal organizations, collective and authority decisions are likely to be far more common than optional decisions [16, p.30].

As stated by [16, p.37], a fourth category is made up of a series of two or more of these types of innovation decisions: contingent innovation-decisions are choices to accept or dismiss that can only be made after a preceding innovation decision has been taken.

1.2.7. The rate of adoption

The rate of adoption is the relative speed at which a social system's members adopt an innovation. It is commonly assessed as the number of individuals who adopt in a given time span [19]. When the number of individuals adopting the innovation over time is plotted on a cumulative frequency basis, the resulting distribution is an S-shaped curve (Figure 3). At first, just a few individuals adopt the innovation in each time period (for example, a year or a month); they are the innovators. However, as more people adopt, the diffusion curve begins to rise. The rate of adoption then begins to level off as less and fewer people remain who have not yet adopted. Finally, the asymptote of the S-shaped curve is reached, and the diffusion process is complete [16].

1.2.8. Diffusion models

In fact, several initiatives and models have been developed to better explain the diffusion of innovation in research. Since the early 1960s, mathematical equation-based modeling has piqued the curiosity of academic researchers. Traditional marketing research has traditionally focused on establishing mathematical models for measurement. Diffusion models of the time were aimed at generalizing explicit diffusion patterns, and hence described the S-curve [20].

Thus, these models aid in forecasting market demand and serve as a decision support tool for a new product's pre-launch, launch, and post-launch strategic choices.

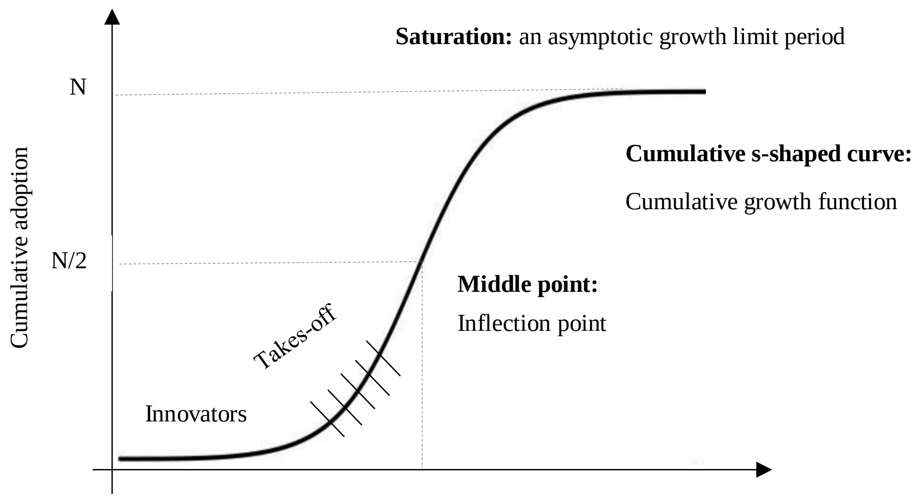


Figure 3. The S-shaped cumulative curve for an adopter distribution

Later, structural approaches arose, focusing on the overall influence of the social network on adoption through factors such as network density, the prevalence of weak ties, or structurally equivalent positions. These models are based on computer science, epidemiology, or sociology. The basic point is that, unlike other alternative methodologies, diffusion prevision models have a common reference in the literature, which is the theory of Rogers. However, each of these models had advantages and disadvantages [20].

Because of a wealth of literature, [20], [23] were able to propose a taxonomy summarizing the state of the art on the subject, dividing the diffusion models into two categories:

the macro and micro models [26], known also by the mathematical models and individual-centered models respectively [1].

1.2.8.1. Macro-level models

It is interesting to mention that the majority of macro-models are inspired by biology, specifically population evolution and disease spread.

The first category of the models was created to predict the future rate of a diffusion. It is composed of a simple mathematical function that explains the accumulation of adopters over time and based on some general features.

The goal is to develop a quantitative theoretical model of the evolution of innovation in a social system among a given collection potential adopters, which simplifies the explanation of such an event. As a result, three models are well-known in this section.

The logistic model. Many models have been developed for presenting the temporal pattern of the diffusion process. These models frequently assume an "S" shaped growth pattern. The logistic function, which has been demonstrated to be a consistent model by empirical study on the diffusion of innovation [20], appears to be the reason of such regularity in development. The logistic model is based on a cumulative S-shaped distribution pattern. It follows a growth model, which is approximated by a function described by the following equation:

$$F(t) = \frac{N}{1+\beta e^{-\alpha t}} \quad , 0 \leq t \leq T \qquad (1)$$

Where t is time; N and α are positive real numbers; β a real, which determines the number of early adopters; N is a numerical upper limit on the size of the growth; the coefficient α is called the internal influence coefficient or imitation coefficient.

The Belgium mathematician Pierre-François Verhulst demonstrated this function in 1845 [20], and the logistic model is credited to him. He claimed that in the early stages of growth, a population would rise exponentially until resources became unimportant. Verhulst hypothesized that the rate of growth is delayed by some function proportional to the size of the maximum carrying capacity, and he created a differential equation for a symmetrical sigmoidal growth curve, which called by the logistic curve [27].

The Logistic curve has a long history of evolution, with various parametric developments occurring when new parameters and variables were introduced to the initial equation [27]. Furthermore, the logistic model is used in numerous researches on the adoption of new technology. This curve is one of the most well-known and widely utilized in the literature [20].

Gompertz model. It is a mathematical model that was published in 1825 by Benjamin Gompertz in his work [28]. The model is an exceptional instance of the logistic function, in which development starts and ends slowly [23]. This sigmoid function approaches the value α gradually [20]. The Gompertz function is denoted by:

$$F(t) = Ne^{-\alpha e^{-\beta t}} \quad ,0 \leq \mathrm{t} \leq \mathrm{T} \qquad (2)$$

Where N, α, and β are positive real numbers.

Gompertz's (1825) formulation is asymmetric and has a fixed inflection point ($F(x) \approx 0.37$). The Gompertz model is simple as well as aggregative. It has been used to model product growth in the diffusion literature, such as Hendry (1972) which forecasted the growth in sales of specific durable products in the United Kingdom. Also, Dixon (1980), who applied the Gompertz function on hybrid grain corn data in the agricultural context [20].

Applications and constraints. The logistic and Gompertz curves are simple. Furthermore, their parameters have been determined from observed incidents and can be usefully interpreted. Indeed, they are founded on simple assumptions that aid forecasters in their endeavors. They are founded on well-defined coefficients [20].

In practice, the logistics and Gompertz function serve as the foundation for product diffusion models; they may be used to analyze the growth rates of various inventions and are frequently used to forecast market trends. To test specific assumptions, these analytical models represent diffusion in an explanatory manner [20].

Although the logistic and Gompertz models have been shown to be reliable in describing the diffusion of innovations in domains such as biology and economics. Bewley and Fiebig (1988) [29], on the other hand, claimed that the logistic and Gompertz curves are overly rigid. They do not explicitly account for the influence of word of mouth or social influence on the adoption process. However, people in the real world frequently accept new products or technologies because they are influenced by others in their social networks. To address this flaw, The Bass model was introduced.

The Bass diffusion model. Frank Bass, an American marketing professor, developed the Bass diffusion model, which was published in the journal ‘‘Management Science’’ in 1969. Originally developed in the marketing arena to model the expansion over time of a new durable good as a result of potential adopters' purchases, its uses have gone far beyond commercial durables, becoming a paradigm for modeling the life cycles of many other types of innovations [30].

To account for the effect of social pressure, Bass defines two driving forces of adoption: innovation and imitation. These explanatory factors reflect the fact that some individuals adopt due to interpersonal persuasion, while others adopt through social pressure from individuals who are already adopters.

Depending on the model, population dynamics are either influenced by the desire to innovate (innovation coefficient *p*, external influence) or by the need to imitate other members of the population (imitation coefficient q, internal influence). To apply it, first determine the size of the market *M* (market potential, or diffusion ceiling), then the innovation coefficients *p* and *q*, and finally the number of adopters at a given moment. The equation is as follows:

$$f(t) = Mp + (q - p)F(t) - {}^{q}/_{MF(t)^2} \qquad (3)$$

Where *F(t)* represents the cumulative adopters at time *t*.

Further precise, the *p* coefficient captures all of the constants that can encourage or discourage people from adopting quickly. These can include communicability, accessibility, cost, good qualities, minimal risk, and a variety of other economic and cultural factors. Some researchers limit the meaning of this variable to the effect of media mass [20]. Internal influence, word of mouth, social contagion, and social influence effects within the group are all captured by the coefficient *q* [20].

Discussion and criticism. However, macro models rely on well-defined coefficients and are concerned with the adoption rate. These models still have a lot of shortcomings. Many mathematical models, for example, are static, which means they do not account for the dynamic interactions and social effects that occur throughout time. Furthermore, they may assume individual homogeneity and miss the social and cultural elements that influence adoption decisions. Also, there is the issue of a lack of network structure, which occurs when mathematical models fail to take into account the social network structure through which information and influence flow. They fail to take into account the fact that individuals are related to others in a variety of ways, and these relationships play an important role in diffusion. Such critical limitations significantly limit the description of the aforementioned models.

To account for population heterogeneity and the network effect, these models are evolving toward approaches known as individual-centered models, which take social structure and communication channels into consideration. The micro-level models are described in depth in the next section.

1.2.8.2. Micro-level models

Micro-level diffusion models concentrate on individuals' interactions and decision-making processes, capturing the heterogeneity in adoption behaviors and the dynamics of diffusion at the individual level. From the literature, three different micro-models were chosen. The section that follows will look at different approaches and their general concepts.

The Threshold model. Threshold diffusion models are a form of micro-level model used to examine the spread of innovations, behaviors, or ideas within a population. They are also known as threshold-based models. The aforementioned models suggest that people have a threshold or critical level that they must reach before they will adopt a new innovation or behavior. This threshold is the bare minimum of peers who have already accepted the innovation that an individual must witness before they are willing to adopt it themselves. The variety of these thresholds, as well as the individual's location in the social network, result in what is known as population heterogeneity.

Historically, the threshold model, sometimes known as the threshold model of collective behavior, was created by the sociologist Mark Granovetter. In 1978, he published an influential work titled "Threshold Models of Collective Behavior" in the American Journal of Sociology [31]. Granovetter offered the concept of thresholds in the context of social influence and collective behavior in this paper.

After that, Valente [32] extended Granovetter's [31] work by stating that an individual's decision is influenced by the conduct of others in the group or system. Because information acquired via intimate networks has a greater impact on individuals. Valente [32] suggests using a direct communication network rather than a system to which the user is a member. The proportion of adopters in personal networks is represented by the exposure *Ei*. It is determined by

$$E_i = \frac{\sum w_{ij} \times y_i}{\sum w_{ij}} \qquad (4)$$

The threshold model developed by Granovetter has been widely employed in the study of a variety of social phenomena, including the adoption of innovations, the spread of rumors, and the dynamics of social movements.

In this regard, it is critical to note that, while threshold models allow for individual heterogeneity, they do not account for the communication process. As a result, individual conversations and interactions are unexpressed notions.

Stated by [20] the interpersonal interactions, such as discussions and conversations, play an important part in the diffusion of innovations. Potential adopters may be convinced or discouraged from adopting an innovation or behavior depending on what they hear from their peers, therefore, these contacts can have an impact. The communication can be crucial in breaking down specific barriers that hinder some people from adopting an innovation.

Epidemiological approach. The epidemiological approach is based on the assumption that the adoption of an innovation—whether an idea, product, or behavior—spreads through a population in a manner analogous to the transmission of a disease. From this perspective, interpersonal contact and social interaction play a crucial role, making the analogy between epidemic spread and information dissemination particularly intuitive.

According to [20], this theory emerged following the publication of Norman Bailey's book (1957) on the mathematical theory of epidemics. Since then, it has served as the foundation for extensive research over the years. Goffman and Newill [33] highlighted the strong analogy between the spread of infectious diseases and the dissemination of information [34]. Moreover, one of the most notable applications of stochastic processes in biology and medicine has been in the mathematical modeling of epidemics [35].

As noted in [36] the diffusion of technology under the epidemiological approach is comparable to the spread of contagious diseases. This approach emphasizes that technology adoption propagates like an infection among potential users. It explains innovation adoption by assuming a homogeneous population of potential adopters. Initially, only a small number of individuals adopt the technology. Over time, non-adopters interact with adopters, and through social contact, the number of adopters increases while the number of non-adopters decreases. Essentially, diffusion occurs as a result of information flowing from adopters to non-adopters. The cumulative number of adopters over time typically follows an S-shaped curve, commonly represented by a logistic growth function [20].

Moreover, the emergence of social norms and collective behavior can also influence the adoption of technological innovations. These social dynamics propagate through networks of interpersonal connections, serving as additional pathways for diffusion [20].

A model-based epidemiological method was developed by [37], who simulated innovation diffusion within a rural social network in Senegal. Their study considered population heterogeneity as a critical factor and concluded that geographical distance does not constitute a significant barrier to the widespread dissemination of information [23].

Other studies, such as [38], focus on social networks and the links through which external factors influence individuals. These works analyze how information propagates from node to node using contagion and exposure models [23]. Additionally, [39] introduced the concept of opinion leaders by analyzing social contagion within networks to predict the future dynamics of new products [20].

The epidemiological approach has also been used to study the spread of rumors, which was first examined in the Daley-Kendall model [34].

Epidemic models. The following paragraphs present the three most significant extension of the epidemic models commonly used in diffusion studies.

- **SI model.** According to [40], many epidemic models discussed in the literature are inspired by the SI model, which represents the most basic epidemiological framework. In this model, a population N is divided into two classes: S (Susceptible) and I (Infected), with $N = S + I$.

In the ‘‘Susceptible’’ state, the person is thought to have contracted the disease from their neighbors. Adoption is more likely to occur when susceptible and infected neighbors are in contact. The contagious phase begins immediately after the contagion has been transmitted.

In the ‘‘Infected’’ state, the person has already caught the disease; as a result, he is contagious and runs the risk of infecting his neighbors. People that aggressively share innovation are infectious [20].

In this model, the disease transmission is determined by both the number of infected individuals as well as the number of individuals who may still be infected. The SI model was used as a foundation for more complicated and representative epidemiological models, and researchers based on it gave birth to three new epidemiological models SIS, SIR, and SEI [40].

- **SI {S,R} model.** In the SIS model, also known as the SI model [20], an ‘‘Infected’’ individual might return to the ‘‘Susceptible’’ class after a period of (recovery) time.

The SIR model added a third state—the ‘‘Removed’’ state—to the ‘‘Susceptible’’ and ‘‘Infected’’ states. The symbol R can also refer to the ‘‘Refractory’’ state, which occurs after a certain amount of infection; in this state, the person is no longer taken into account because he may never be able to recover the infection or transmit it again, or the opposite. Retired (removed) people are aware of innovation but have no desire to promote it [20].

- **SEI model.** According to the SEI model, a person is first ‘‘Susceptible’’, then becomes ‘‘Exposed’’ for a latency period, followed by ‘‘Infected’’. Additionally, the exposed class also includes people who are infected but are not yet infectious. When the suspension period is over, the individual becomes infectious in the sense that he is able to transmit the contagion [20].

Despite the fact that this strategy is easy to understand, and several models have used it as their foundation. Traditional epidemic models, however, have a number of limitations that have prompted the development of new more complex models to better capture the spread of innovations in a population.

In fact, epidemic models frequently assume a perfectly mixed population where everyone has an equal chance to contact with one another, which tends to simplify social interactions. Although it may be helpful to grasp certain fundamental features of how epidemics spread, this simplification may grossly underestimate the complexity of actual interactions. Furthermore, populations are frequently diverse in terms of social connections, behaviors, and other important traits.

In addition, classical epidemic models generally presuppose uniform transmission, which holds that the probability of transmission is uniform between all individuals. On the other hand, it's possible that in reality, certain people have a higher influence or impact on the spread of the disease than others.

As such, these deterministic models can not account for the significant variances that exist in various situations measuring certain times. In some cases, the models that describe the evolution time of interactions and the reaction of individuals are significantly more appropriate, like cascade models [20].

Cascade model. The primary principle behind the cascade model is that at any time a neighbor v of node u adopts, node u will follow suit and adopt with a probability of ($p_{u,v}$). Alternatively said, there is a possibility that node u will decide to make a purchase every time one of his neighbors does [41].

Cascade model is a well-known model used to examine how knowledge spreads and is adopted over time among networks of connected people. This category of models presupposes that innovation spreads via information cascades and that social behavior happens when a series of people carry out the same activity while ignorant to signals from their private information [20].

In this model category we distinguish two often used models; the Independent Cascade (IC) model, and the Linear Threshold (LT) model.

The Independent Cascade Model (ICM). The Independent Cascade Model is additionally referred to as the susceptible/infected/recovered (SIR) model [42]. Each network edge, in this model, is related with a probability of influence. When individuals accept an innovation, they only have a single possibility to influence their neighbors. The influence is described as a stochastic process in which the neighbor will adopt the innovation with probability *p*. If the neighbor adopt, their related probabilities can influence their neighbors, resulting in a cascading effect.

It's probable that, at originally, individuals have no motive to adopt because they didn't have any private or public information. However, as more people approved, prospective adopters may have rationally reasoned that there were compelling reasons to do so based on information from the social network. This method can explain at least part of the phenomenon of imitation [20].

The Independent Cascade Model is commonly used in the analysis of viral marketing, word-of-mouth marketing, and information transmitted via social networks.

The weighted cascade model. The weighted cascade model, also known as the weighted independent cascade model, proposed by [5] is a variant of the independent cascade model that is used to study information diffusion in social networks. Each node in the network has a weighted degree of impact in this model, which defines its ability to disseminate information to its neighbors. Mathematically, $\Sigma W_{i,\ entrant} \leq 1$, the total sum of the incoming weights of each node is less than or equal to 1[20].

The Linear Threshold Model (LTM). The LTM has been considered as one of the fundamental cascade model, and it has been widely used in studies to better explain the dynamics of information, behavior, and innovation spread in networks. It is worth noting that the model has a long history of development by a variety of researchers. Rather, it has evolved over time as a result of contributions from numerous researchers in fields such as sociology, economics, and computer science. [5] is most likely one of the academic papers that helped to create or apply the LTM in a particular context. The model is sometimes referred to as Schelling's Model, after Thomas C. Schelling, who introduced it in the context of racial segregation.

The model works as follows; the individual is influenced by each neighbor according to a uniformly random non-negative weight in the interval [0,1]. If the sum of the degrees of influence exceeds their own threshold, it will be active. This degree of influence is imperative for the individual to become an adopter. For each stage of the simulation, a sequence of active individuals activates their neighbors in the same way, and so on. Propagation ends when there are no more inactive person [23].

$$\sum W_{i,j\ incoming}\ (Y_J)\ \geq W_i \qquad (5)$$

Both of these cascade models (ICM, LTM) have been extensively researched and implemented in a variety of areas to better understand how information, innovations, or behaviors spread across social networks. They provide useful insights into the processes of influence and diffusion, helping researchers and practitioners to develop more effective techniques for boosting adoption or controlling information flow across networks. On the other hand, a problem linked to the cascade model is that the system remains irrevocably stable; active nodes cannot shift to inactive states, and activated nodes cannot deactivate. Even more, at moment ‘‘t’’ all active nodes have the capacity to activate the others. In reality, individuals do not accept innovation simultaneously.

1.2.9. Discussion and criticism

Since the inception of the theory of innovation diffusion, researchers and scholars have been diligently working to create models that precisely capture the complex dynamics of how innovations diffuse through populations. An innovation diffusion model's major objective is to predict the future evolution of this process, which occurs in both space and time. According to [43] description, the stated goal of innovation diffusion model is to depict the successive increases in the number of adopters given of a set of potential adopters over time, and predict the development of an already in progress diffusion process.

Because of the multi-faceted nature of innovation adoption, various models have been developed. In our research, the innovation diffusion models are classified into two sub-divisions; macro-level models or mathematical models, such as the Logistic, Gompertz, and Bass model. Traditional mathematical models seek to represent aggregate patterns rather than individual decisions. Many of these models are based on the Bass framework, which is one of the most influential marketing models. The Bass model was created to forecast sales of new consumer durables. The model assumes that if a person has not yet accepted a product, the probability of doing so is directly related to the number of previous adopters [44].

The fundamental weaknesses of these macro-level models is their simple assumptions and failure to account for the heterogeneous dynamic nature of individual adoption behaviors, social relationships, and changing external factors. To overcome these shortcomings, innovation diffusion models are progressing toward approaches known as individual-centered models or micro-level models, which represent the second sub-division of innovation diffusion models in this research.

As indicated by [39], the diffusion model based on individuals can be a new approach to analyzing the interdependence of networks and final behavior [20]. Micro-level models concentrate on how individual members of a group behave and make decisions. In the context of innovation diffusion, micro-level models provide a granular perspective by focusing on the decisions and interactions of individual actors. These models dive into the complexities of how individuals decide whether to adopt or reject an innovation.

Threshold models assume that individuals have a certain number of adopters in their network, and that once this number is reached, they will accept the innovation. This illustrates the theory that adoption spreads more widely once a threshold is crossed, because people are influenced by the behavior of a critical mass, though the thresholds are generated informally, they may explain the S-shape of the adoption curves. As a consequence, threshold models took a special interest in the social system, giving it a distributed probability in order to generate heterogeneity. However, the difficulty is how to achieve this for a personal network with a tiny number of adopters and limited interaction [20].

To examine the spread of innovations as if they were contagious diseases, epidemic models are used. They consider people to be ‘‘infected’’ with the innovation and examine how interactions between them lead to the spread of the innovation. Mathematically, this phenomenon is best described by an S-curve and it can be simply generated from an adoption frequency table. Epidemic models are especially efficient at capturing the effect of interpersonal relationships on adoption decisions. Thus, the impact of communication channels is central to the epidemiological approach [20].

In cascade models, when one person adopts an innovation, it might set off a chain reaction of adoptions via social networks, so, the collective behavior will emerge. These models are especially important in the context of social media, as information and trends can travel quickly across interconnected networks.

Agent-Based Models (ABMs) are versatile and can capture the heterogeneity and complexity of real-world adoption scenarios by simulating the actions and interactions of individual entities (agents) to observe emergent patterns at the macro level. Each agent in the model represents an individual with distinct attributes and decision-making rules. ABMs have solved many of the problems encountered at the micro level [20].

Chikouche [20] underlines a significant issue of existing diffusion models, which is linked to innovation ignorance. The models listed above do not take into account the many attributes of innovation, however relative_advantage, compatibility, complexity, trialability, observability, and reinvention are critical. These models highlighted that theoretically, but not explicitly, innovation exists in design.

In reality, individuals are naturally different, displaying a complex tapestry of variances in their social behaviors, interactions styles, and communication methods. Furthermore, people' decisions and decision-making processes range greatly, owing to a variety of factors such as personality traits. This inherent variation provides richness and complexity to human interactions, emphasizing the individuality of each person's journey in the fabric of social dynamics. However, existing diffusion models disregard this fact. They rely on the principle that the decision to adopt an innovation will be made given that others have already done so without personal evaluation, and individual choices in all of these models are driven by social pressure. This is a significant limitation that needed to be taken into considerations.

Another important shortcoming of literature models is that they necessitate some adopters to begin simulation; which can be considered as opinion leaders, these adopters are chosen at random. The real social system, on the other hand, clearly demonstrates that this sort of adopters has additional features, such as people who are more extraverted being more likely to positively influence the process of diffusion. For that reason, a selection based on appropriate assessments is required, that are primarily based on the varied personal traits of each category of adopters.

Furthermore, it should be noted that existing diffusion models typically fail to respect Rogers' stages of decision-making. In real terms, the individual's journey to a final decision is a complex process with multiple stages, each of which results in changes in the individual's values and characteristics. Diffusion models may oversimplify this process by disregarding the complexity involved in each decision-making phase. Moreover, Rogers emphasized processes such as knowledge, persuasion, decision, implementation, and confirmation. In actuality, however, these phases are not necessarily linear or evenly progressing. Individuals may return particular stages, reassess their values, and modify their traits during the decision-making process, making precise modeling of this dynamic trip difficult.

It is also noteworthy that the diffusion models assume a static social system, whereas the individual was originally dynamic, with the ability to form relationships and release others at any time.

Another negative point at the level of the social system used by the models in the literature, is that the heterogeneity of the targeted population or potential adopters appears itself in a limited way due to significant differences in the values of perceived innovation characteristics. However, in diffusion modeling, it is imperative to understand that heterogeneity comes from the diversity of communication and interaction behaviors, the perception phase, the personal evaluation of the innovation, decision-making, as well as the variety of values present within individual characteristics. Current diffusion models do not fully capture this complexity.

1.3. Overview of Agent-Based Modeling (ABM)

According to [46], aggregate models like Bass model, which offer generalizations based on differential equations have limited utility, as they cannot answer "what-if" questions or account for consumer heterogeneity and complex social dynamics that shape diffusion . Criticisms of these models extend to their inadequate predictive and explanatory power, suggesting a restricted ability to accurately predict and explain real-world outcomes. Moreover, their inability to address a wider range of theoretical issues, meaning they might not cover all the relevant aspects of the phenomena they are modeling. In response to these challenges, recent years have witnessed the emergence of Agent-Based Modeling (ABM for short) or Agent-Based Simulation (ABS) – sometimes called Multi-Agent Simulation or Multi-Agent Based Simulation; as a more general notion, also the term Agent-Directed Simulation may be applied [47]- as promising alternatives. These approaches offer opportunities to overcome the limitations of traditional models [48], paving the way for new avenues of research in diffusion studies.

Typically, agent-based models are simulations that depict the dynamic interactions between groups of people, usually a large one. They were first created as a research tool for complexity theory, and throughout the past decade, they have become more and more well-liked in a variety of scientific fields [44]. Even though the concept of multiple interacting agents has been known since the 1940s, with John Vonn Neumann's work on cellular automata, ABS did not become popular until the early 1990s [49].

It should be highlighted that ABM is not synonymous with object-oriented simulation, despite the fact that the object-oriented paradigm provides an appropriate medium for the construction of agent-based models. As a result, Agent-based systems are generally object-oriented. ABMs are subsets of the larger category of individual-based models [45].

Simulation can be defined as experimenting with or running a model. In agent-based modeling and simulation, the concept of multi-agent systems is applied to the basic framework of simulation models [47]. It focuses on the principle that complex systems can be represented by individual agents with complex and diverse behaviors, giving rise to global emergent behavior as a result of the interaction of agents within themselves and their surroundings [49].

According [50], Agent-based models are computer programs in which artificial agents interact based on a set of rules and inside an environment defined by the researcher. Whereas these rules and restrictions determine predictable behavior at the micro level, interactions between individuals and their surroundings regularly aggregated to form unexpected social patterns. Moreover, [51] define agent-based modeling as a mind-set that involves describing a system from the perspective of its component units rather than a specific technology. These micro-level units are referred to as "agents" and might be any type of actor [52].

1.3.1. An introduction to Agent

What exactly is an agent? Notwithstanding it has been a popular area of study in recent years, there is no uniform definition of agents and their fundamental characteristics within the scientific literature since many inter-disciplinary authors describe agents based on their own particular field and required specifications [45] [49]. Definitions, on the other hand, tend to agree on more issues than they differ on [45]. For example, [53] defines an agent as a computational entity, comparable to a software program, with the ability to perceive and act on its environment. It is autonomous, which means that its behavior is influenced to some degree by its own experience [52].

Agent characteristics are difficult to extract from the literature in a consistent and unambiguous manner due to the diversity of their uses, as agent-based models are typically explored from the perspectives of its constituent pieces. [45] describe and briefly explain the following features that are common to most agents:

- Autonomy: agents are self-governing entities (i.e., not influenced by external control) that possess the ability to process and exchange information with other agents to make independent decisions. They are free to communicate with other agents in limited contexts, and this does not necessary affect their autonomy [45].
- Heterogeneity: in ABM, characteristic heterogeneity refers to the agents' various features and qualities that distinguish them from one another. Attributes, behaviors, states, and interactions are examples of such traits.
- Active: the term ‘active’ refers to agents that have independent influence within a simulation. The ability of active agents to make decisions and execute actions depending on internal rules, goals, and information available to them is a key feature.

Likewise, [49] identifies the fundamental characteristics of agents as reported across a wide range of studies. These characteristics are grouped into two main categories: (i) location, which includes situatedness and mobility, and (ii) behavior, which encompasses autonomy, reactivity, proactivity, sociality, and adaptability. Other attributes, however, have not reached a consensus in the literature regarding their classification as essential agent properties [45]. It should be noted that the selection of agent characteristics ultimately depends on the specific objectives and attributes of the system being modeled.

1.3.2. Rules, Relationship, and Behavior

Each agent can have rules that determine their behavior and interactions with other agents and/or their surroundings. A single rule set can be applied to all agents, or each agent can have its own set of rules. Rules are often built around 'if-else' statements, with agents performing an action once a specific condition is satisfied [45].

Relationships can be defined in a variety of ways, ranging from simply reactive to goal-directed. Agent behavior can be planned to occur synchronously, which means that each agent executes actions at each discrete time step and all change happens at the same time, or asynchronously, in which each agent's activities are scheduled by the actions of other agents and/or in relation to a clock [45].

1.3.3. Agent environments

Environments define the space in which the agent's actions take place. The agent interacts with other agents and its environment, receives feedback, and adapts its behavior in response to changing environmental conditions. It refers to the agent's surroundings or external context, and covers anything outside of the agent that may influence or be influenced by the agent's activities.

1.3.4. Agent-based simulation application domains

ABS is a versatile and multidisciplinary field with several applications in domains such as social sciences, economics, ecology, and other industrial and military fields [49]. Agent-based models enable researchers to study clearly how and why a given set of interactions among individuals achieves some collection result [50].

Schelling (1969) was the first to consider individuals in a simulation in the social sciences. In his scenario dealing with residential segregation, he presented a neighborhood modeled by squares in a grid, each of which can house an individual (household). The eight neighbors for each household are observed in terms of how many share a certain household attribute (in Schelling's case, skin color). If this number falls below a certain threshold, the household is moved to an unoccupied spot in the grid at random. This process is continued until no more households move.

The basis of ABM, in particular, originate in the simulation of human social behavior and individual decision-making. In this manner, ABM has changed social science research by enabling researchers to reproduce or generate the development of empirically complex social phenomena at the micro-level using a set of very simple agent-based rules [45].

Since agent-based modeling allows fine-grained modeling of the interactions in social networks, This simulation model is increasingly being used in innovation diffusion research [54]; it is used to explore and examine the process of innovation diffusion [55], and it allows for the accounting of micro-level innovation drivers by modeling adopters' behaviors and attitudes in a social network [54]. Then, it was demonstrated that it is particularly suitable for diffusion studies [20]. Two benefits of using the ABM paradigm in the study of innovation diffusion are that it makes it easier to simulate agent heterogeneity and allows for more detailed modeling of interactions mediated by social networks.

In fact, agent-based modeling has been implemented to help building theory, as tool analyzing real-world scenarios, to improve decision-making, and generate policy recommendations [46], [52], [54].

As we have discussed above, Agent-based models (ABMs) and simulations have become extremely powerful tools in various fields, particularly in the study of complex systems and phenomena such as diffusion. In this context, ABMs provide a dynamic and adaptable framework for modeling the spread of innovations, ideas, diseases, or behaviors through the interaction of individual agents within a population. These models capture the heterogeneity and adaptability of agents, allowing researchers to explore the fundamental mechanisms and dynamics of diffusion processes. In recent years, agent-based modeling has gained popularity and several notable works have employed it to examine the diffusion phenomena.

1.4. Personality traits theory

≪ Personality is like a charioteer with two headstrong horses, each wanting to go in different directions≫

Martin Luther King, Jr.

1.4.1. Definition

The term personality stems from the Latin word Personare, which originally meant of an actor's voice speaking through a mask [56]. Personality according to [57], American psychologist, ‘‘is a stable and organized set of psychological traits and mechanisms that impact an individual's interactions and adaptations to their psychological, social, and physical surroundings’’ [1], [58]. Moreover, in the words of Trainer (1957), personality is the result of a person’s behavior in social contexts [56].

Personality is a crucial factor in the human being, it determines their reactions and emotions towards important facts around them [57]. It includes not just their outward behaviors but also their overall response patterns to external stimuli [56]. This spiritual entity draws a person’s psychic image and contributes to the determination of their future behavior in the various situations they may encounter [57]. Under this umbrella term, we frequently discuss people’s attitudes, behaviors, and emotions [57], which set them apart from other.

In accordance with psychoanalysis, an individual's personality forms throughout his life, with the first eleven years being a critical period. Sharing experiences and interactions with other individuals continue to contribute the personality formation [57] [1].

Philosophers in Ancient Greece attempted to understand human individuality by detecting and categorizing differences in behavior and emotion [59]. However, researchers are still studying human character today, but from a more conceptual standpoint, to assess an individual's tendency to act. In this regard, two approaches are distinguished, the topological approach and the trait approach [58].

The topological approach divides people into personality categories, with each person belonging to only one at a time [58]. In contrast, the trait method seeks to identify individuals through the use of personality dimensions that encompass all the characteristics of a person. These dimensions are known as ‘‘personality traits’’, and they are used to categorize individuals based on the degree to which each attribute manifests [60]. Individuals are classified in all dimensions in the trait approach, as opposed to the topological approach [1], [58].

1.4. 2. Literature review on personality traits models

Over the years, several theories have been developed to characterize personality and identify its characteristics [61]. The systematic examination of personality traits introduced by Gordon Allport and Henry Odbert [62] in 1936, who compiled a comprehensive list of 4,500 terms defining personality traits in their seminal work Trait-names: A psycho-lexical study. Their research laid the groundwork for later psychologists to start defining the fundamental aspects of personality, and highlighting the significance of characterizing personality in terms of measurable qualities.

In 1943s building on Allport’s work, [63] utilized factor analysis to reduce this list to sixteen traits, ultimately resulting in the establishment of the 16 Personality Factor Questionnaire (16PF). Many psychologists investigated Cattell's list and discovered that it could be further reduced.

[64] reduced personality to three higher-order traits: psychoticism, extraversion, and neuroticism. Parallel to this development, Isabel Briggs Myers and Katharine Cook Briggs developed the Myers-Briggs Type Indicator (MBTI), which gained popularity in the 1970s. The MBTI divides people into 16 different personality types based on four dichotomies: extraversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving. Despite the MBTI is useful in organizational psychology, professional development, and marketing due to its simple type-based categorization, it poses challenges for quantitative prediction and computational modeling.

In the 1980s, Lewis Goldberg [65] adopted the term "Big Five", arguing that the five dimensions — openness, conscientiousness, extraversion, agreeableness, and neuroticism — covered the most significant elements of human personality. Goldberg also created the

International Personality Item Pool (IPIP) that was open-access items for measuring these characteristics.

The most influential advancement came with McCrae and Costa work [60]. They validated the Big Five model using multiple tools and observers, demonstrating its adaptability and cross-cultural applicability. To measure the Big five factors, the McCrae and Costa introduced the NEO Personality Inventory (NEO-PI, and later NEO-PI-R), a shorter and widely used questionnaire. These tools help standardize the empirical assessment of the Big Five, offering continuous scoring for each feature and are frequently utilized in psychology, education, and organizational research. Subsequently, the IPIP-NEO was developed as an open-source alternative, allowing for greater accessibility and research uses.

In the early 2000s, [66] proposed an extension of the Big Five into the HEXACO model, including a sixth dimension—Honesty-Humility—alongside Emotionality (similar to Neuroticism, but incorporates sentimentality), Extraversion, Agreeableness, Conscientiousness, and Openness. The model captured moral/ethical characteristics that were often ignored by the Big Five. Its primary tool, the HEXACO Personality Inventory (HEXACO-PI and HEXACO-PI-R), provides precise measurement, making HEXACO particularly useful in practical domains such as organizational psychology, ethics, and behavioral research.

1.4.2.1. The OCEAN personality model (McCrae, 1987)

The OCEAN model, often known as the "Big Five" or the "Five-Factor model" (FFM), established by McCrae and Costa in 1987, has garnered a great deal of attention, it has been examined across various populations and cultures, and is still the most commonly accepted theory of personality today [56]. It is now considered the gold standard for studying and analyzing personality [1], [59]. Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism are the five broad personality traits included in the model. Each attribute is made up of multiple components or personality traits (Figure 4)

- **Openness to experience (O).** This factor reflects a preference for intellectuality, which includes attributes like critical thinking, novelty, esthetics, and curiosity. As well as an appreciation for art, emotions, adventure, imagination, self-awareness, individualism/nonconformity, originality, and a variety of interests and information-seeking tendencies [1], [65], [66].

Individuals with high levels of openness are receptive to new ideas and use the facts gathered to make judgments and decisions rather than depending solely on existing knowledge. They are also less sensitive to anchoring bias. Individuals with high openness are more likely to display an open mindset to new, challenging ideas compared to those with middle or low openness [7].

- **Conscientiousness (C).** Is the amount to which individuals value planning, have persistence and pursue success. It is the reflection of the tendency to following rules, compliance, goal-oriented behavior, and organization versus spontaneity [1], [57], [66]

People with high levels of conscientiousness are thoughtful and patient. They examine what is happening and develop strategies based on how it affects and influences others [61].

- **Extraversion (E)**. Extraversion signifies a preference for interpersonal relationships and is associated with excitement, vitality, self-confidence, positive emotions [1], and sociability. Individuals with high levels of this attribute are enthusiastic and tend to communicate and express themselves. They engage in environmentally friendly behaviors [61] and have many friends; more specifically, they may receive information from the ever-increasing social resources [7].
- **Agreeableness (A).** This feature presents how much people appreciate compassion, cooperation with others, social harmony, honesty, decency, obedience, easygoingness, and trust [1], [7], [65], [66].

Individuals with high degrees of agreeableness are more likely to have a positive outlook on human nature, and are also more thoughtful of others and lack independent thought [7], [68].

- **Neuroticism (N).** Is the exact opposite of emotional stability [1], the extent to which individuals endure unpleasant feelings, and the tendency to emotionally overreact [68]. Neuroticism is a personality trait that describes a person who is unhappy, moody, emotionally unstable, angry, anxious, impatient, depressed, anxious, insecure, and vulnerable [1], [61]. Individuals with high neuroticism are more likely to experience negative emotions [7].

Notably, this model (OCEAN) does not divide people into five parties, but rather examines them five times, each independently of the others, in order to give an approximate overall picture of the character of the person. Each factor is made up of several traits or aspects, and each perceived trait of a personality is either equivalent (+) or opposite (-) of one of the factors (such as the nice and naughty traits of the agreeable factor) [67]. Personality psychologists generally agree that these five criteria appear to represent significant individual differences in the human personality [69].

With the introduction of the OCEAN model, there has been renewed interest in the study of personality traits under a variety of contexts. The five-factor model has been the subject of numerous studies using a variety of personality assessment, and it seems to be a robust taxonomy of personality. It has been demonstrated to predict a variety of significant factors to industrial and organizational psychologists [67]. In addition, the OCEAN model has been investigated in order

Trait	Facets
Openness (O)	Fantasy
	Aesthetics
	Feelings
	Actions
	Ideas
	Values
Conscientiousness (C)	Competence
	Order
	Dutifulness
	Achievement striving
	Self-Discipline
	Deliberation
Extroversion (E)	Warmth
	Gregariousness
	Assertiveness
	Activity
	Excitement seeking
	Positive emotions
Agreeableness (A)	Trust
	Straightforwardness
	Altruism
	Compliance
	Modesty
	Tender-mindedness
Neuroticism (N)	Anxiety
	Angry hostility
	Depression
	Self-consciousness
	Impulsiveness
	Vulnerability

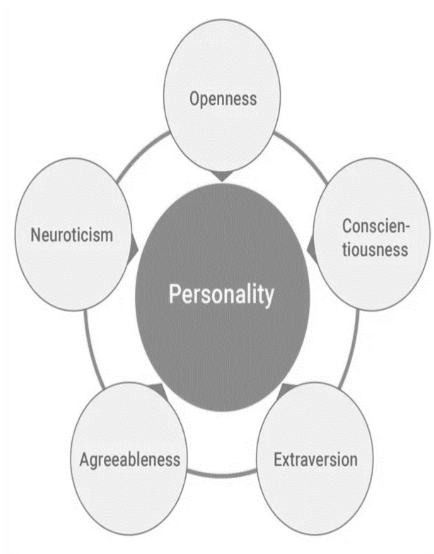


Figure 4. OCEAN model.

to examine the impact of personality factors on the intention and behavior of adopting innovations [70], including the use and adoption of technology [7], the adoption of information seeking behaviors [7]. Likewise on work performance and employees' well-being [69], [71], and individual innovativeness and satisfaction with life perceptions.

1.5. Conclusion

When an innovation; either a new ideas, activities, services, or objects; are invented, diffused, adopted, or rejected, an essential question comes to our mind ‘‘Why do certain innovation succeed and are accepted while others fail and are rejected ?’’

Innovation diffusion theory provides a solid framework regarding how new product, idea, or service progressively soaks into societies and cultures, beginning from its introduction to its full adoption.

In this chapter, we have; in detail; outlined the diffusion of innovation theory. Innovation, communication, time, and social system, as per literature, are the four key principles of this aforementioned theory. In this regard, we presented each element separately.

Innovation are defined along with its characteristics; relative_advantage, compatibility, complexity, observability, and trialability; which are known as the perceived innovation attributes. In addition to the five attributes mentioned previously, researchers have also identified other characteristics that may influence the diffusion and adoption of innovation, including cost, divisibility and communicability, social approval, and profitability. However, it is agreed that the five characteristics are the main perceived attributes of innovation, and each character has included quite of few other characteristics. Separating and taking into account a single characteristic independently of the others is not advisable to predict the future of innovation. Therefore, researches advised to possess more positive characteristics for increasing the chances of adoption.

Communication is a critical process in diffusion theory; it can be viewed as a techniques of influence and persuasion. It allows the transmission of information about the innovation’s qualities, benefits, and applications. It takes place via various channels, which vary based on the context of the innovation and the target audience. Notably, innovators need to comprehend the social system's characteristics and preferences, in order to select the most relevant communication channels for efficiently diffuse their innovations.

The time dimension is defined as a key factor of the theory, it is presented with the adoption curve. The number of individuals who adopt an innovation over time is plotted on a cumulative frequency basis, yielding an S-shaped curve. The individual decision-making cannot be made immediately, it requires time and follows Rogers' five-phase model, which starts with the knowledge phase, persuasion, decision, implementation, and ends by the confirmation step.

Individuals do not adopt the innovation at the same time, they can adopt it in a chronological sequence. They can be categorized in different categories based on their willingness to adopt the innovation. As per literature, there are five categories that define the innovation diffusion cycle including innovators, early adopters, early majority, late majority, and laggards. Each of these classes reflects a collection of people with a specified and numerous of characteristics, as well as the amount time they take to be an adopter.

Historically, with the emergence of the innovation diffusion theory several models have been developed to further explain the theory and accurately capture the complexity of the diffusion process. In this chapter, diffusion models are divided into two classes, the macro-level models and micro-level, or mathematical and individual-centered models respectively. The first category; macro-level; comprises three well-known models, the Logistic, Gompertz, and the Bass models. Mathematical models rely on well-defined coefficients and are concerned with the adoption rate. Besides, they fail to capture the heterogeneity of individual adoption behaviors, social relationships, and changing external factors. As a result, researches evolved through an individual-centered approach. This section includes three models: Threshold, Epidemic, and Cascade. Micro-level models focus on individual interactions, decision-making processes, and capturing individual variety in adoption behaviors.

In present chapter, a comprehensive overview on agent-based modeling was provided to establish a solid foundation for the subsequent that followed. The detailed explanation of agent-based simulation served as the basis methodology used in this study. By analyzing this component separately, a more complex understanding was achieved.

` In order to carry out the bibliographic research and correctly frame our contribution, we devoted the third part of the chapter to offering a state of the art on the personality trait aspect. We carefully explained the term personality psychologically, likewise, referencing prior researchers' definition.

In this section, we highlighted that two approaches are distinguished, topological approach and trait approach. We focused on trait approach. Under the trait approach, individuals are identified using dimensions known as personality traits. These traits classify individuals based on the extent to which each attribute manifests.

Since 1936, different theories have been introduced to characterize personality and identify its attributes. Starting with 4,500 terms with (Gordon Allport and Henry Odbert, Trait-names: A psycho-lexical study). Following that, Raymond Cattell (1943) reduced them to sixteen traits. Later, many psychologists reduced Cattell's list to only five traits. McCrae and Costa (1987) confirmed the model's validity and provided the model we currently use “The Big Five” or ‘‘OCEAN’’ personality model.

OCEAN is the abbreviation of Openness to new experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism that are the five factor approved in the personality model. It is underlined that each factor consists of numerous components or personality traits. As observed next, we have attached the corresponding list of characteristics to each of them. The Big five model has proven to be an effective framework that psychologists may use in both industrial and organizational settings. For instance, the model has been applied to examine innovation adoption behavior, individual innovativeness and life satisfaction, and work performance.

In the next chapter we present theoretically our proposed model, illustrating the global model’ architecture and precisely capturing the progression of our innovation-decision making process. Then, we implement this theoretical model using randomly initialization.

Chapter 2. Proposed model: A personality-driven innovation diffusion model

2.1 Introduction

The ultimate objective of all creators of innovation is to assure its diffusion, which is at the heart of diffusion theory. One of the fundamental key questions is ‘‘What explains why certain innovations succeed in reaching large segments of the population, while others fade into obscurity before being recognized by even a small minority?”

Innovation diffusion has long been an important subject of study in social science, it aims to explain how and why novel ideas, products, or behaviors propagate across individuals and groups. The fundamental question is ‘‘what is the right method to integrate this theory into a system that takes into account the important concepts? Furthermore, how can we model human behavior as a process influenced by other adopters?’’. Whereas numerous theories have looked at socioeconomic, demographic, and cultural factors influencing this process, an essential dimension has often been neglected, the individual personality.

In this work, the principal objective is to address this shortcoming. We concentrate on the development of a new theoretical model that integrates the personality traits to better comprehend the diffusion of innovations. Our approach recognizes that human characteristics, such as openness to experience, need for novelty, and risk tolerance can play a determining role in how people adopt and disseminate ideas or technologies.

This chapter is mainly articulated into two sections. The first section presents the conceptual foundations of our model, describing how we combine the OCEAN model of personality traits with Rogers' model of innovation diffusion, and highlighting the manner in which personality traits are conceptualized and integrated into the analysis of innovation diffusion. The value of this perspective arises from its ability to emphasize observable individual differences in the process of innovation adoption. By integrating personality dimensions, our model aims to provide a more nuanced and holistic understanding of the mechanism underlying this complex phenomenon. The second section presents and discuss the results of the implementation of our proposed model in a baseline case, in which we have simply used randomly generated values to simulate the model.

2.2. Overall view of the proposed model architecture

Our thesis work aims to examine and analyze the process of adoption of innovation among individuals where individuals' personality traits are taken into consideration.

In our model (see Figure 5), individuals are represented by agents with specific profiles. This profile includes the agent's identity (id), and the adoption state that indicates whether or not the agent has already adopted the innovation. In addition, a set of characteristics linked to the innovation known as the ‘‘Perceived innovation characteristics’’. Furthermore, the agent profile comprises a type of agent personality presented by the five major personality traits (OCEAN).

Innovation has been taken with its general definition without specifying any particular type, it refers to anything regarded as novel by a potential adopter, whether it is an idea, product, service, information, or technology. For that reason, we present the innovation by the same theoretical framework as Rogers did. Relative_advantage, Complexity, Compatibility, Trialability, and Observability are the five innovation characteristics.

The main factors that have an impact on agent's decision to accept or reject an innovation are their perceived innovation qualities, the innovation characteristics themselves, and their personality attributes. In accordance to the global architecture (Figure 5), the individual decision-making process goes through four phases. More details are provided in the following section.

2.3. Decisional process

In life, people do not change their beliefs immediately, but rather gradually over time. Since the diffusion of an innovation is a complex change affecting a broad population, this micro process is the result of elementary individual decisions [72]. Due to this nature, the decision does not occur instantly, but follows a process of incremental change [73] which may be influenced by users' personal preferences or by the value of the innovation itself.

In the research on internal influence models, diffusion is defined solely in terms of interpersonal communication and social interactions between prior adopters and potential adopters. Thus, the internal influence model is more appropriate when an innovation is visible in the social system [20]. Personal preferences are not considered; only the social plane is concerned.

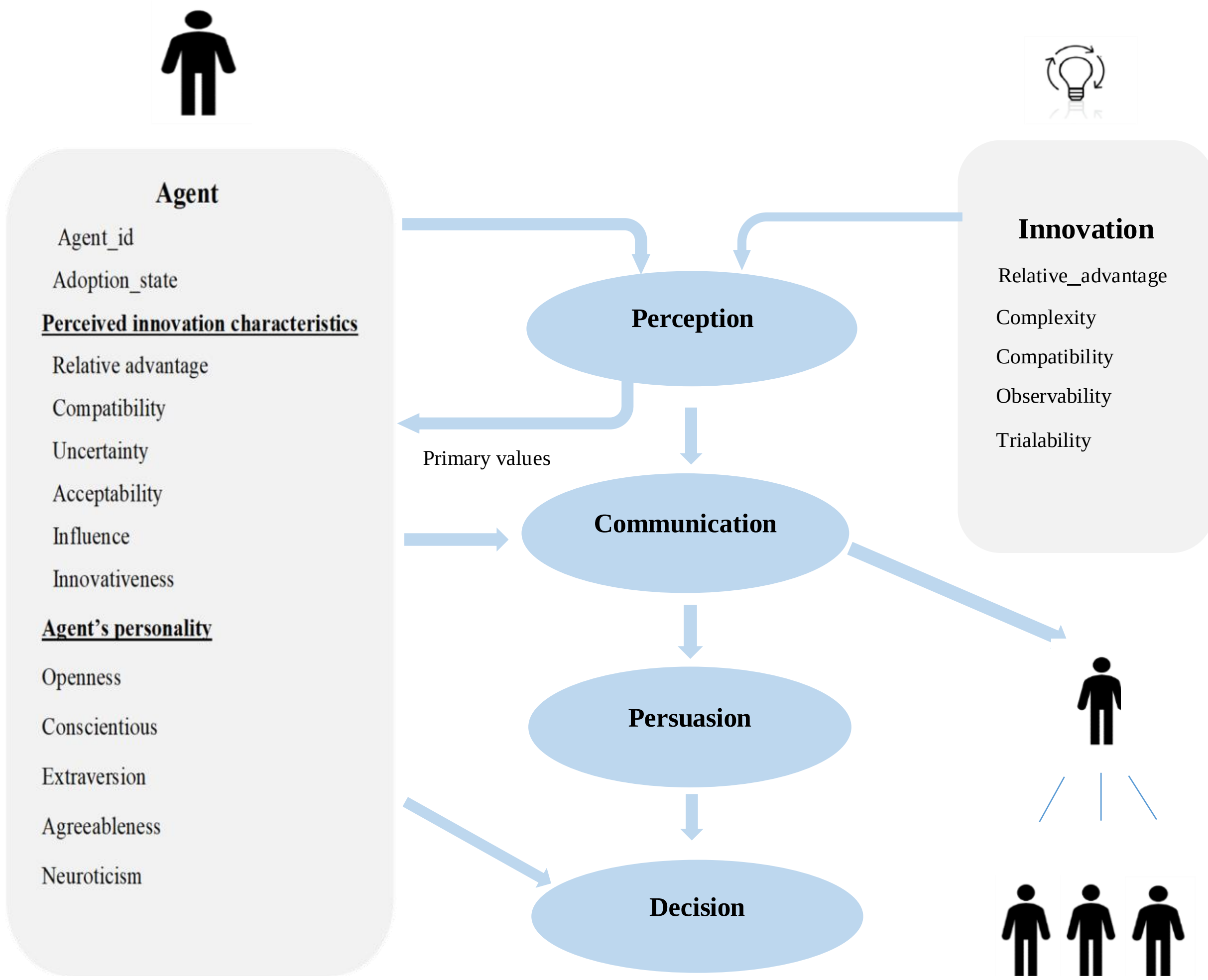


Figure 5. Global architecture.

Indeed, these models regard adoption to be pure imitation [43]. This work emphasizes this limitation, paying special attention to it; unlike existing models, which imply an extreme transition from non-adopters to adopters.

The individual decision-making process in our proposed framework, goes through four stages (see Figure 6), beginning with perceiving the innovation, seeking additional information about it and reducing ambiguity and uncertainty through communication with the social system, evaluating the level of persuasion of this innovation, and finally making a decision. This process has been formally established (for more details see Section. 2.6.).

Additional concepts which are critical for the proper functioning of the model have undoubtedly been incorporated into the proposed framework, such as communication behaviors, social system and susceptibility to social influence, individual differences, as well as personality characteristics.

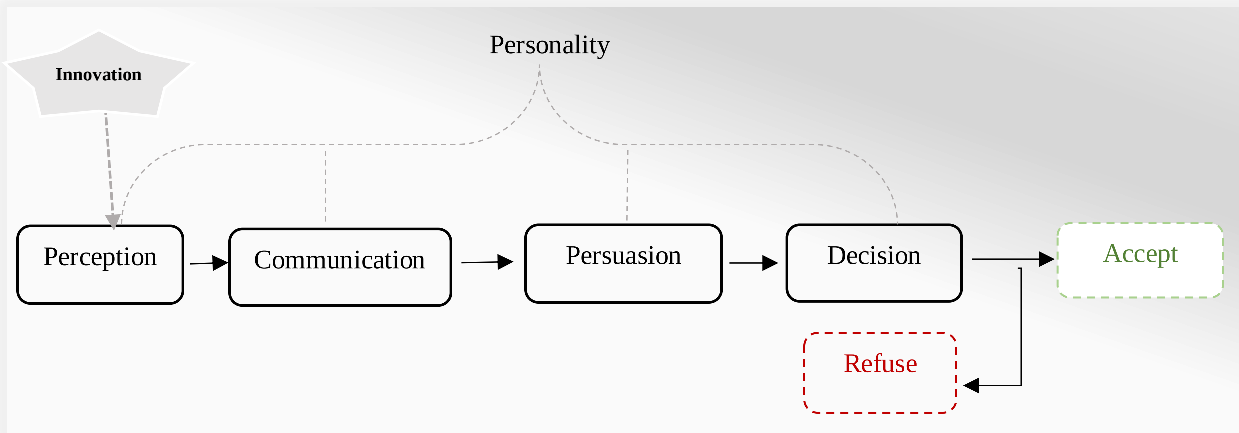


Figure 6. Individual decision-making process.

2.4. The individual's (or agent's) social neighborhood

The term social neighborhood refers to the immediate social environment of an individual, which includes people they regularly interact with this individual. Cellular automata (CA) [74] can be an effective method for modeling social neighborhoods and comprehending social dynamics. When used in social contexts, CA can simulate how individuals (agents) interact with their neighbors and how these relationships change over time. CA is made up of a grid, with each cell representing an individual (agent) from social environment. The cell's neighborhood consists of nearby cells to it.

Cellular automata theory typically considers two types of cell neighborhood, Von Neumann’s and Moore’s neighborhood. Applying Moore neighborhood in cellular automata model; ensure that each cell’s state is influenced by its eight immediate neighbors. This can produce more complicated and interesting patterns than using a simpler neighborhood, such as the Von Neumann neighborhood, which just considers the four orthogonally neighboring cells.

In our work, the Moore neighborhood type is metaphorically used to symbolize an individual's social environment, with each agent (person) typically surrounded by eight neighbors. However, the precise number of neighbors and the nature of relationships can differ due to the individual's personality traits.

2.4.1. Personality traits and social connections

≪ Talking to a good friend, playing with your child, discussing a project in a work group.........., Interacting with others is arguably one of the most prevalent and important contexts of our lives.≫

Mitja D. Back (2023, P.03), Social Interaction Processes and Personality

Social relationships are one of the most important aspects of our lives [75]; in fact, since humans are social beings, life would be impossible without others [76].

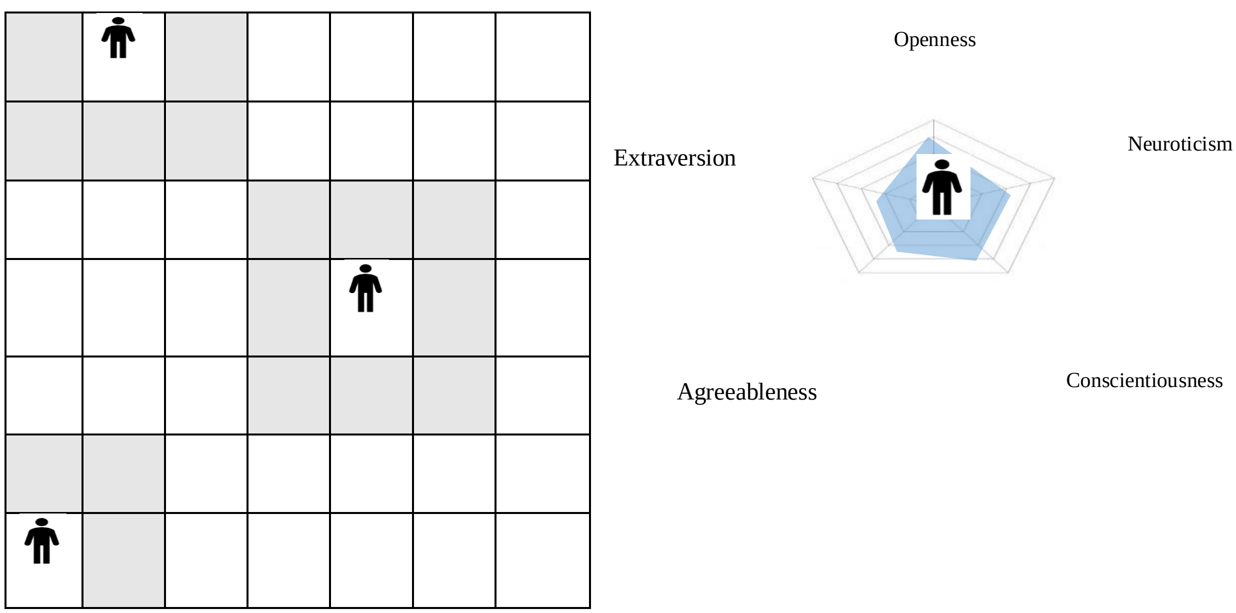
Individuals do not acquire social connections at random. Rather, they are inextricably linked to the development , behavior, and effects of personality [75]. Individuals' personality traits, on the other hand, influence both the quality and quantity of their interactions, and these factors have an effect on personality in reverse [76].

In scientific analyses of social relations, a number of recent conceptual and empirical discoveries have contributed to a greater understanding of how personality is defined, expressed, developed, and exerted through social interaction processes [73]. For instance, personality traits have been scientifically linked to a variety of life outcomes including mortality, divorce, occupational attainment [77], life satisfaction [78], and other aspects of subjective well-being [79].

In our framework, we have linked an individual's social connection to the Big Five personality traits, in which each personality feature influences how many and what kind of social interactions a person maintains, as well as effectively incorporate the impact of personality traits on individual' susceptibility to social persuasion and influence.

A continuous cellular automate is illustrated in (figure 7. (a)), each cell symbolize an individual (agent) within a social community. Hence the personality attributes of extraversion, neuroticism, agreeableness, openness, and conscientiousness were assigned to each agent (figure 7. (b)). We have typically used the Moore neighborhood, which includes the center cell and the eight cells that are immediately neighboring the center cell.

It is worth noticing that the size of a person's social network differs depending on their personality characteristics. High neuroticism generally associated with anxiety, moodiness, and emotional instability. According to a multitude individual level research findings, peoples with this personality character might have a few close social connections [76] resulting in a smaller effective social network, given that their nervous and anxious exterior makes it challenging to develop and maintain relationships.



(a) Agent Moore neighborhood. **(b)** Agent five personality traits.

Figure 7. Agent social network.

On the other hand, extraverts, for example, may have more friends [80] and social interactions. Initially, because they regard others as more fascinating, leading them to embrace new friendships. Secondly, extraverts may act more expressively, creating the appearance that they are more intriguing, enable others to more frequently accept them as friends [75]. In our agent Moore neighborhood, an extravert may interact regularly with all eight neighbors, and perhaps even beyond, by creating a large and active social network.

Individuals who are agreeable and conscientious prefer to be cooperative and organized, respectively. However, they may have fewer and close, but more meaningful, stable, and positive relationships with their neighbors, resulting in a close-knit community.

Persons with a high openness to experience are open-minded, imaginative, and eager to try new things. They may promote new ideas and activities to their Moore neighborhood, fostering creativity and innovation among neighbors. They can additionally form a diversified group of friends and participate in a variety of activities, resulting in a vibrant and eclectic social network. Individuals with extremely high openness have a higher probability to form new contacts. As a result, they have a larger network of relationships.

2.4.2. Personality traits and social influence

Social influence is defined as "the science of influence, persuasion, and compliance" [81]. It is the process through which one person' behavior is influenced by that of another. [82] describes it as ‘‘the process by which individuals adapt their opinion, revise their beliefs, or change their behavior as a result of social interactions with other people’’. According to social influence theories, conformity to group norms is a key factor in explaining individual behavior [83].

In social psychology, the relationship between personality traits and the susceptibility to social influence is still being addressed [84]. Personality is additionally viewed as a significant piece of knowledge in building effectiveness persuasive systems due to people's reactions to persuasive stimuli may differ depending on their personalities [84].

As cited in [81], several studies have been undertaken to study the link between personality and social influence [85], [86]. Hovland et al. [84] performed systematic research on personality and persuasion, concluding that people with high levels of neuroticism whom frequently feel inadequate and depressed are more influenced and susceptible to persuasion. Likewise, those with a high openness trait [87]. On the other hand, studies looking at the relation between extraversion and persuasion have yielded contradictory results; some indicate that it has a detrimental effect on persuasion [87], while others argue that extraverts are more susceptible owing to their desire to be socially desirable [64].

Moreover, [88] found that conscientious persons are less susceptible to social persuasive technologies. In the other hand, as per [59] conscientious individuals tend to exhibit goal-directed behavior, including planning, organization, and adherence to rules and conform to social norms which makes them more likely to be susceptible to influence from others. Individuals that are agreeable are additionally inclined to agree with the opinions of others, causing them to better apt to follow to social norms [1].

These contradictory findings highlight that the relationship between personality traits like neuroticism and extraversion and susceptibility to social influence and persuasion can not be generalized, but is indeed complex and context-dependent, varying depending on the study setting and methodology. It is not feasible to definitively evaluate whether each feature has a positive or negative relation with social influence without evaluating the specific context of the study.

2.5. Integration of Rogers' innovation diffusion theory with OCEAN (Big five personality traits) model

Decision making is a crucial part of people's lives [89]. In the face of challenging and novel innovations, the decision to adopt these innovations or reject them is the result of decision-making process which influenced by a several of factors. Personality characteristics may be a major drivers of the human behavioral decision-making. Moreover, traits including conscientiousness, openness, neuroticism, extraversion, and agreeableness greatly shape how individuals approach decision-making and react to uncertainty [90].

Several researchers investigated the relationship between personality traits and decision-making styles, using a variety of measurement tools and methodologies [89], [91], [92], [93], [94], [95]. As a results, they found that personality traits significantly impact on how decision-making are made [89].

In this work, one of the primary objectives is to examine the role of personality dimensions on decision-making processes. For this reason, we successfully combined the Rogers innovations diffusion model with the OCEAN personality traits model in order to present a new innovation diffusion model (ss Eq.(6)). We used the Rogers' model as a theoretical framework to represent the innovation and individual' perceived innovation characteristics with different attributes and characteristics. However, The OCEAN personality traits model has been used to capture the individual personality profile (as shown in Figure 5)

$$ID = f\big(\,IC, PIC, IP(Big\ 5)\big) \qquad (6)$$

Where the individual decision (ID) is a function (f) of three main factors: Innovation Characteristics (IC), Perceived Innovation Characteristics (PIC), and Individual Personality Traits (IP) based on the OCEAN model. Notice that the factor IC includes compatibility, complexity, trialability, observability, and relative_advantage of the innovation, while IP includes openness to new experience, conscientiousness, extraversion, agreeableness, and neuroticism.

As previously discussed, innovation is anything that potential adopters view as novel. Rogers identifies five key features that can be used to represent innovation. Similarly, our framework employs the following factors to characterize innovation:

2.5.1. Innovation five attributes

- ***Relative_advantage.*** This is a randomly generated value, ranging from 1 to a certain ceiling, that varies from agent to agent and is added to their profile.
- ***Complexity***. It is chosen as a fixed real number from 0 to 1. It denotes the innovation complexity.

- ***Compatibility.*** It is also a fixed real number between 0 and 1, where a value of 0 indicates complete incompatibility with the innovation and 1 indicates full compatibility.
- ***Observability.*** It arises when communication takes place, and we assume that if an agent communicates with an adopter, they observe the innovation's results.
- ***Trialability***. It is chosen as a fixed real number from 0 to 1 that is uniform for all.

2.5.2. Agent profile

The agent presents an individual, the majority of the necessary characteristics that define an individual are present in the following agent profile:

- ***Agent_id.*** The agent's identifier. Each agent has a unique identifier.
- ***Adoption_state.*** A boolean value (0 or 1) that represents the agent's adoption state, indicating whether he has already adopted the innovation or not.

2.5.2.1. Perceived innovation characteristics

After perceiving the innovation, the agent's perception of its characteristics is presented by the following values:

- ***Relative_advantage***. Takes the same value of the innovation relative_advantage, as we consider it to be the same.
- ***Uncertainty.*** Represents the agent's uncertainty towards the innovation.
- ***Acceptability.*** Means the individual's desire to adopt the innovation and it takes a value between 0 and 1.
- ***Compatibility.*** Refers to the degree of harmony an individual perceives with the innovation. It value ranges from 0 to 1.
- ***Influence.*** It picks a random real number in the interval [0,1] to represent the level of the social influence.
- ***Innovativeness.*** In our framework, innovativeness is defined as "the degree to which an individual is relatively earlier in adopting an innovation than other members of their system" [68]. According to [68], innovativeness is a permanent trait that affects how a person views and responds to innovations. We include innovativeness as a characteristic

of our agents, and it is related to the trait of openness to experience. It takes a value between 0 and 1.

2.5.2.2. Agent personality

In this study, we utilized the Big Five (OCEAN) personality model, to reflect an individual's personality. The model consists of five traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, each assigned a value between 0 and 1 through random selection.

- **Openness to experience.** Openness to new experiences trait plays a crucial role in innovation adoption field. In our modeling, agents that are open to new experiences are defined as being generally preferring challenges, more intellectually curious, broad-minded, creative, more willing to take risks, and appreciative of novelty, all of which are necessary characteristics for the perception and successful adoption of innovation. As a result, adopting innovation and being open to new experience are closely related traits.
- **Extraversion.** An extravert agent is an active person, friendly, loves to talk, meets new people, and may begin conversations. He further has an active social life, enjoy social interactions, participate and socialize. These traits enable him to display a better social presence, communicate more effectively, and have larger network. Because of the nature of these characteristics, we positively linked the extraversion personality trait with interpersonal communication and social relationships.
- **Conscientiousness.** Literally, the conscientiousness trait interacts with susceptibility to social influence and persuasive strategies. Conscientious agents, known for their tendency to exhibit self-discipline, responsibility, goal-oriented behavior. These may lead them to conform to social rules and norms, indicating a propensity to be influenced and persuaded by others within their social group.
- **Agreeableness.** Agreeable agents are characterized by traits such as kindness, cooperativeness, prioritize maintaining harmony within social groups and positive social interactions and relationships. Due to these traits, agreeable agents may be more receptive to social influence.

- **Neuroticism.** Neuroticism refers the tendency to experience negative, distressing emotions [96]. Agents with higher levels of neuroticism likely to have social network deficiencies, reporting more unpleasant interactions and spending less time in pleasant relationships with others. Neuroticism affects social network size and perception of loneliness, signaling that higher neuroticism levels are linked to higher loneliness, fewer friends, and poorer social adaptation.

Agents with higher degrees of neuroticism have lower levels of social adaptation and satisfaction over time, including less social connections and increased feelings of loneliness. According to research, neuroticism is connected with low interpersonal trust, which may hinder social interactions. Agents with higher neuroticism levels may have difficulty developing and maintaining interpersonal relationships. This loss of social support, limited social networks and increased feelings of loneliness, resulting in decreased social influence and persuasion capabilities. As a result, neuroticism is a key trait in our modeling that is associated with interpersonal communication and social influence and persuasion.

2.6. The proposed innovation decision-making process

The decision-making process is viewed as a cognitive process that involves reasoning, critical thinking, and prioritization based on values, preferences, and beliefs. In the context of innovation diffusion innovation, an effective individual decision-making process necessitates a personal evaluation of the innovation, in which the perceived innovation characteristics and the psychological aspect of the person represented by the personality dimensions play a dominant role. Furthermore, the effects of interpersonal communication and connections, as well as social influence and persuasion, have a greater impact on this process. Because of this, our suggested individual decision-making process seeks to collect all of these factors to demonstrate that the decision to adopt or reject an innovation does not occur immediately, it is done gradually following a set of steps. Our decision-making process consists of four phases, as described in what follows.

2.6.1. Perception

Humans exhibit a wide variety of personality traits, which can influence their innovative behavior. Openness to novel experience (openness in short) is a fundamental feature of human personality. The personality literature highlights the positive correlation between openness trait and risk-taking and various expressions of creativity, showing that openness has been linked to the individual perception of the innovation, resulting in individuals have different experiences with and orientations toward innovations. These unique individual difference are what is referred to as individual innovativeness. Additionally, individual innovativeness is also enhanced by personal characteristics [97], [98], individuals with greater openness trait scores are more innovative and more likely to come up with innovative product ideas [98].

For individual with high innovativeness trait value, their acceptability value for a new innovation will be higher. This makes sense, as they are likely to be early adopter and consider the new innovation acceptable. This is consistent with the theory of diffusion of innovation, which argues that early adopters and innovators are critical to the diffusion of new ideas. Furthermore, they will typically have a lower uncertainty value due to that such individuals are less likely to feel uncertain or nervous about adopting innovations since they are more comfortable to change and novel experiences. Their curiosity and openness to trying new things usually result in a reduced perception of uncertainty associated with the innovation.

Our objective in the perception phase is to detect early adopter category under particular conditions. We use the openness to experience value as a benchmark to assess the values of other personality traits.

It was our hypothesis that those who scored highest on the openness score would be innovative, more likely to accept and engage in novel experiences, and more willing to take risks and tolerate uncertainty. These people would hold a great appreciation for novelty and adaptation and consider uncertainty as a normal part of life [99]. Their compatibility with the new will therefore be of great value.

Procedure 1:

If** (Openness to experience = maximum_value)* ***then *// Openness to experience will take value in the interval [0.75,1] or [75%, 100%] we use the two notation*

Innovativeness ← Innovativeness_ max

Acceptability ← Acceptability_ max

Compatibility ← Compatibility_ max

Uncertainty ← Uncertainty_ min

// if the agent has a maximum value of the attribute openness then its values of innovativeness, acceptability and compatibility will also take a maximum value in the range [0.75, 1], on the other hand uncertainty attribute will take a min value in the interval [0,0.2]

End If

If** (Compatibility ≥ 0.9) and (Accepetability > Uncertainty)* ***then

Adoption_state ← Adopter

End If

Figure 8. Perception algorithm.

2.6.2. Communication

As is commonly known, novelty frequently comes with ambiguity because there is not enough complete information available. Communication is one of the best strategies to reduce uncertainty. Communication involves direct interaction between persons, which lowers the uncertainty regarding the innovation and increases its relative_advantage [20].

We are focusing on personality traits and social connections relationship in this phase. Usually, we show how a person's personality traits affect the amount of interpersonal communication they engage in. For this reason, every Big Five characteristic is linked to a certain social network interval (for additional details see Section. 2.4.1).

2.6.3. Persuasion

Humans differ in their interpersonal relationships which deeply intertwine with personality traits. Personality characteristics have significant influence on interpersonal communication skills [100]. As evidence, people's communication styles often reflect their personalities and character traits. Ultimately, individuals might influence or be influenced by surroundings. In the social psychology context, the relationship between personality traits and persuasion is still under exploration [84], [101].

Procedure 2:

```
If (Neuroticism ≥ 0.75) then
    | number_agent_neighbors ← random.choice [0,2]      // the number of neighbors in this case will be
    |                                                    either    0, 1, or 2
Else If (Openness to experience ≥ 0.75) or (Extraversion ≥ 0.75) then
    | number_agent_neighbors ← 8
Else
    | number_agent_neighbors ← random.choice [3,7]      //will be either 3,4,5,6, or 7
End If
```

Figure 9. Communication algorithm.

Personality further serves as an important piece of knowledge in developing effectiveness persuasive systems due to people's reactions to persuasive stimuli may differ depending on their personalities [82]. The objective of this phase is to examine how personality qualities, specifically neuroticism, conscientiousness, and agreeableness, impact social influence and persuasiveness. Depending on the values of their personality qualities, the agent receives various degrees of influence after interacting with their neighbors.

We hypothesize that those who score highly on neuroticism are frequently more prone to emotional instability, anxiety, and heightened stress sensitivity. Because of these characteristics, they may avoid relationships or situations that could make their stress or anxiety worse. As a result, they may limit their connections with others. Consequently, they are less susceptible to peer influence and social networks than people with more extensive social networks.

In the context of our model, neuroticism traits reduced the susceptibility to influence value. However, based on [1], [59] we propose that conscientiousness and agreeableness traits raise the influence level.

2.6.4. Decision

At the last stage of the diffusion process, the agents have a thorough awareness of the innovation, as well as the key values that allow them to determine whether to adopt or reject it.

Procedure 3:

```
While (number_agent_neighbors ≠ 0) do
    If (Neuroticism ≥ 0.75) then
      | Influence ← Influence_ min          // the attribute influence will take the min value in the range [0, 0.2]
    Else If (Conscientiousness ≥ 0.75) or (Agreeableness ≥ 0.75) then
        | Influence ← Influence_ max
    End If
    Observability ← 1
    Uncertainty ← Uncertainty – Trialability
    Relative_advantage ← Relative_advantage + Influence
End While
```

Figure 1O. Persuasion algorithm**.**

Procedure 4:

```
If (Compatibility ≥ 0.9) and (Uncertainty ≤ 0.1) then
  | Adoption_state ← Adopter
Else If (Acceptability ≥ 0.75) and (Uncertainty < 0.20) and (Relative_advantage > 0) then
    | Compatibility ← Compatibility_max
End If
```

Figure 11. Decision algorithm**.**

2.7. A schematic representation of the suggested algorithm

Aiming for a more detailed approach to the recommended innovation diffusion process, we designed a schematic diagram (Figure 12) that illustrates the execution of our suggested algorithm. We additionally sought to make sure that our algorithm was simple to facilitate its understanding and its graphical interpretation.

This figure shows six stages. A process is represented by the rectangle symbol in this modeling, but the persons' list or collection is represented by the oval symbol. Moreover, we used the rhombus symbol to signify a condition that will be checked. Two formats of lines are used in our presentation. The bounded oriented line represents the program's flow in addition to the rigorous oriented lines that we utilized to show how personality traits and communication affect later stages. A pointed regular hexagon was utilized to represent a certain process or action, namely the selection of an agent (x), following which this agent (x) will engage and converse with neighbors inside their social system.

We first randomly generate a population to begin our simulation. Next, we use the perception procedure (For more details see the Section 2.6.). The main objective of this phase is to extract the list of early adopter agents who exhibit the characteristics of an early adopter. After that, we focus on the Non-adopters population to complete the execution of our program stages. We select an agent (x) who will communicate and interact with neighbors in the social system environment in order to obtain more information about the innovation, decrease his uncertainty value, and increase the relative_advantage value. We then correlate that agent's communication behavior with extraversion, neuroticism, and openness to new experiences trait.

After interacting with their neighbors, the agent reaches a particular level of influence, this influence value varied according to the personality traits values like neuroticism, conscientiousness, and agreeableness, this is the persuasion phase. In order to determine whether or not the agent will be an adopter, we lastly evaluate the agent's compatibility and uncertainty levels.

In the following section, we put the model into practice. We define the various methods and tools used during the implementation process. Subsequently, we discuss the results of the simulation.

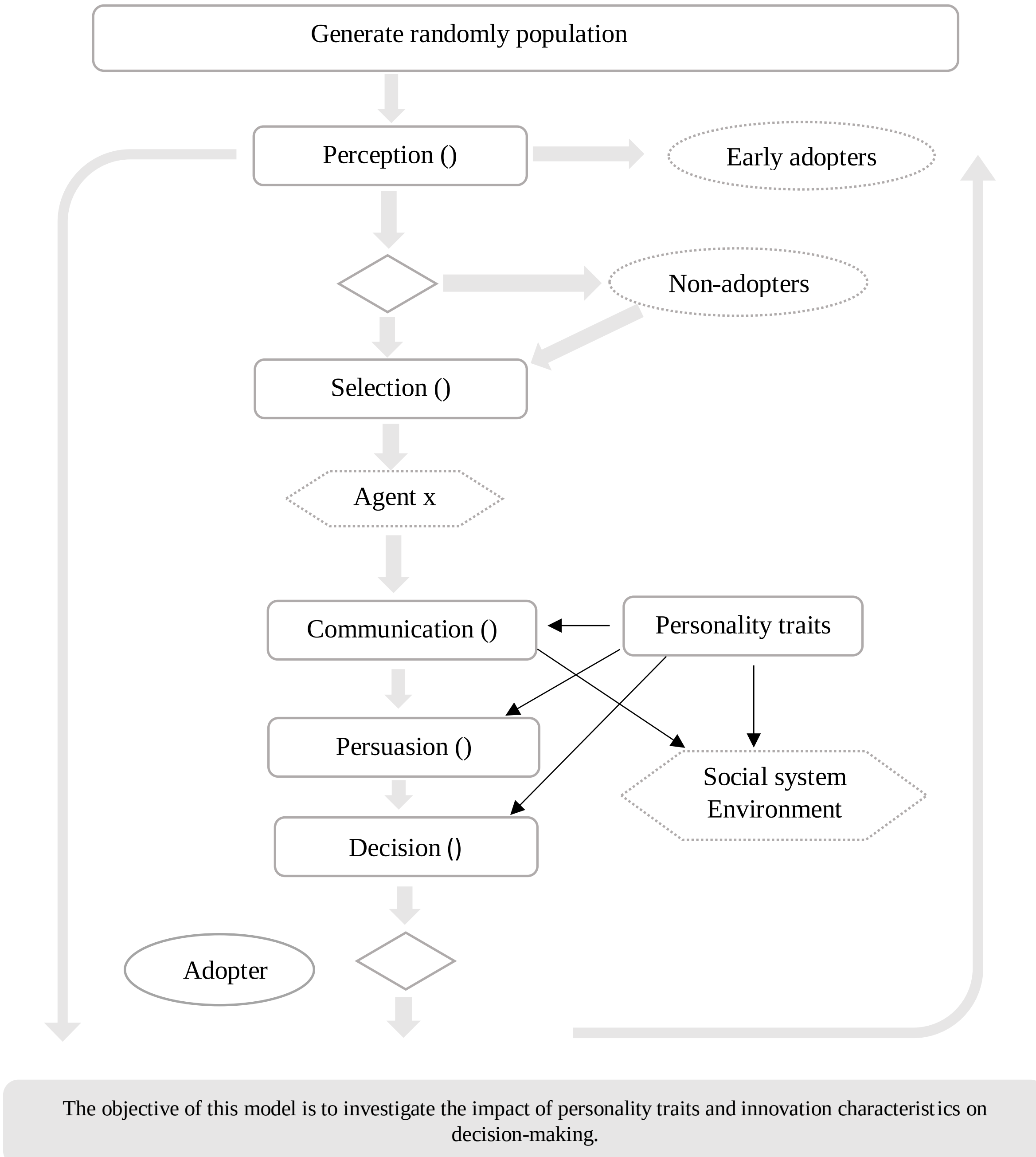


Figure 12. Schematic diagram of the proposed algorithm.

2.8. Implementation and results using randomly initializing.

2.8.1. Implementation setup

Python, a popular programming language, is used to implement the model in this study. According to [102], Python is powerful that may be used for large-scale development projects. Python programs are also simpler, smaller, and more adaptable than programs developed in other popular languages [100, p.20]. In our experiment, we employed the Jupyter IDE and the Anaconda Navigator, the most well-liked open-source Python distribution platform.

The implemented code launches a server with an interactive interface upon execution. This interface displays a grid representing the agent environment, along with their characteristics outlined in the "Agent profile" section. Each agent is represented by a circle, colored blue if it is adopter, and red if it is not. The simulation can be controlled by the user, who can choose to start, stop, or advance the simulation by a single step. Additionally, the user can create the population by selecting the desired environment density and speed of advancement (Figure 13).

When the simulation is executed, the user can observe the color of the agents on the grid changing from red to blue, indicating that non-adopter agents have adopted the innovation. The simulation generates graphs in the chart section, which display the number of adopters and non-adopters over time. As the simulation progresses (Figure 14), the curve representing the number of adopters (the green curve) begins to rise, while the curve representing the number of non-adopters begins (the red curve) to decline.

2.8.2. Results and discussion

We have performed a number of simulation scenarios. We changed the system settings in these scenarios in order to see how the simulation results vary.

For validation purposes, we choose particular scenarios. The First scenario (Initial scenario) was chosen as it provides a fundamental reference point for evaluating the algorithm's performance by assessing its behavior under standard conditions, without taking into account the influence of personality factors. This allows us to gauge the algorithm's effectiveness and robustness. Furthermore, to address the issue of selecting early adopters and opinion leaders, we implement separate experience scenarios for each.

After carrying out several simulations, it became clear to us that the openness to experience factor is a crucial requirement for both the perception and communication process. Another important aspect of perception and persuasion procedures is neuroticism trait. Conscientiousness and agreeableness characteristics are also important during the persuasion phase. For that reason, we present the following scenarios related to these traits.

Figure 13. Simulation interface.

Initial scenario.

For this run, we selected a population of 1000 agents, each equipped with a list of randomly generated attributes. To start the simulation, we assigned a percentage of 25% of agents that have already adopted the innovation, while the remaining 75% represented non-adopter agents. When we observe the adoption curve from t = 0 to t = 6 (shown in Figure 15), we witness a steady increase. At t = 0, only a fraction of agents had embraced the innovation. However, as time passed, the adoption rate increased significantly, reaching an interesting inflection point around t = 6. This increase in adoption indicates that a critical mass of agents understand the benefits or value proposition of the innovation. Following that, at t = 7, we noticed a stabilization in the adoption curve, indicating a saturation point where the bulk of potential adopters had already integrated the innovation into their daily routines. Notably, our basic model, which excludes complex influences like individual personality traits, converges on a 50% adoption rate. This finding underscores the logical and consistent flow of our basic model.

Figure 14. Adopters/Non_Adopters curve.

Scenario 1.

The selection of opinion leaders group in literature models is done at random; this step necessitates reasonable evaluations**.** Selecting opinion leaders for successfully disseminating an innovation requires examining their personality traits and strategically matching them to the innovation's attributes to increase the adoption rate. Opinion leaders frequently play a crucial part in the diffusion of innovation. Their influences can have a considerable impact on the acceptance rate of new ideas, products, or technology within a given community.

An opinion leader; in our model; described as an agent who has already adopted the innovation and whose primary responsibility is to exert a sizable degree of influence within their network, including the ability to influence the opinions of their neighbors. Beyond that, we have added supplementary personality factors to this category. The specific traits and characteristics of opinion leaders can indeed shift depending on the sort of innovation and the context in which it is introduced.

To shaping the effect of opinion leaders' personalities on the influence of peer opinions and decisions, as well as to ensure the validity of our proposition. We simulate the following scenario.

With a population of 1000 individuals, we assigned 75% as non-adopters and 25% as opinion leaders (as we assigned above in Initial scenario to show the difference in results). In this case, opinion leader is adopter agent who is also extraverted individual. Opinion leaders with high extraversion are energetic, socially inclined, and enjoy the company of others. They prosper and feel at ease in relationships, and they frequently maintain a happy and engaging manner. Comparing the resulting adoption rate (Figure 16) of this scenario to the curve of the preceding scenario (Figure 15. Initial scenario) where such considerations are absent demonstrates that strategically choosing opinion leaders through logical examination improves and increases the adoption rate, which supports our proposition. Note that in both scenarios, we used the same population and sub-division.

This demonstrates that extraverted opinion leaders are more likely to drive adoption rates for innovations requiring for social interaction, community engagement and frequent user interaction. Their persuasive communication style and propensity for thriving in social situations enable them to persuade others to adopt the innovation. The findings of this case study illustrate that the diffusion process can be greatly accelerated by selecting opinion leaders based on innovation features, especially when the innovation is driven by social factors.

Scenario 2.

The aim of this scenario is to evaluate the factor of the openness to new experiences society. As previously indicated, our goal is to examine how the five personality qualities affect people decisions. For this experiment, we assume that 75% of agents have the highest level of openness trait. Individuals with high openness character are innovative personalities and more likely to immerse themselves in unusual experiences.

Following the execution of the scenario, the results depicted in (Figure 17) suggest a significant correlation between openness to new experience and innovation adoption. The adoption rate curve increased and stabilized at t = 11, indicating that the highest adoption percentage was achieved at that point in time.

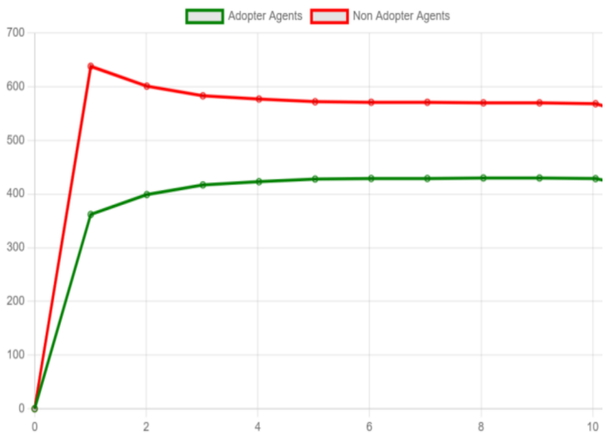


Figure 15. Initial scenario. The result of the basic algorithm. The innovation adoption rate with a population of 1000 agents, 25% adopter agents and 75% non-adopter agents. Without accounting for any influence.

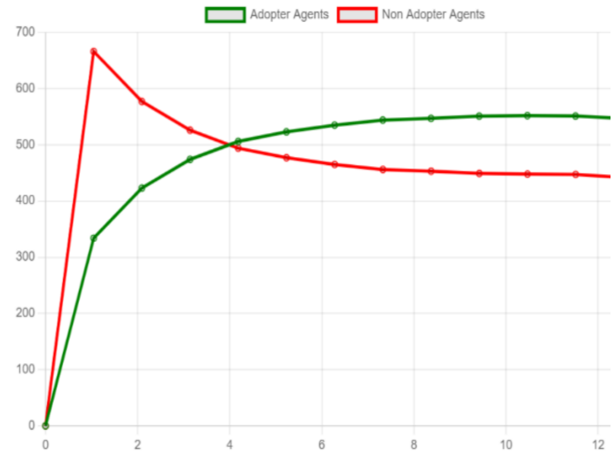


Figure 16. Scenario 1. The innovation adoption rate with a population of 1000 agents, 25% opinions leaders and 75% non-adopter agents.

These findings support our earlier suggestion that societies with a greater openness to new experiences tend to be more innovative and adaptable. Individuals with high openness traits may be more willing to take risks and embrace new innovation. This propensity towards novelty and innovation not only promotes a more dynamic and innovative society, but it also raises the adoption rates of innovations.

Furthermore, these results underscore the crucial importance of nurturing a culture of openness within a society, as it appears to be a key driver of innovation and adaptability. In conclusion, the relationship between openness to new experiences and innovation adoption is dynamic, offering valuable insights into the factors that influence a society's acceptability of innovations. Therefore, the early adopter category is closely linked to the trait of openness to new experiences.

Scenario 3.

In contrast to the previous scenario (scenario 2), this one assumed that the population being studied had reached the highest level of neuroticism, characterized by erratic emotions and difficulty in communicating with others.

The findings gleaned from this scenario, as illustrated in (Figure 18) show a clear contrast with scenario 2, where openness to new experiences significantly increased adoption rates. Here, neuroticism leads to less peer influence and a lack of exposure to new ideas, resulting in a longer and lower overall adoption rate.

The findings of this scenario reveal a substantial correlation between high levels of neuroticism and lower rates of innovation adoption. Individuals with high neuroticism frequently exhibit unstable emotions and have less social relationships, limiting their exposure to innovation. Their unwillingness to participate in social networks, as well as their predisposition to reject external influences, particularly those from opinion leaders, limit their opportunity to get informed about novel innovations. The lack of social connection and exposure considerably reduces their readiness to adopt innovations. These results highlight the relevance of social stability and connectivity in fostering innovation uptake. Societies with high degrees of neuroticism may have considerable challenges in adopting new ideas and technology, emphasizing the necessity for measures that promote emotional stability and social interaction in order to boost innovation diffusion.

Scenario 4.

The findings from this experiment provide valuable insights into the relevance of personality traits, specifically neuroticism, conscientiousness, and agreeableness, in the context of persuasive dynamics. Our study aimed to determine how these traits influence an individual's susceptibility to persuasion and social influence. We hypothesized that individuals with high levels of conscientiousness and agreeableness would be more susceptible to persuasion, while those with high levels of neuroticism would be less susceptible.

Regarding conscientiousness and agreeableness, our results indicated no significant impact on adoption behavior (see Figure 19). These findings align with previous research by [59], suggesting that these traits alone do not explain differences in persuasion susceptibility.

Contrastingly, our hypothesis on neuroticism received empirical support. Individuals with high neuroticism scores exhibited limited social influence and ineffective communication skills. This finding aligns with our previous scenario (Scenario 3), which also highlighted weak peer influence and poor communication among highly neurotic individuals.

Figure 17. Openness to experience situation. Hypothesis testing for the influence of Openness to new experience trait on individual's innovation adoption, 75% of agents have the highest level of openness trait.

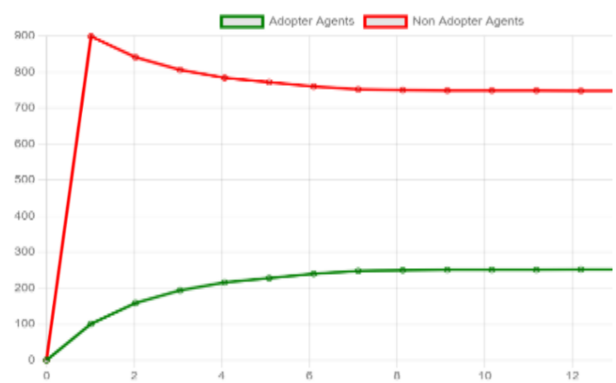


Figure 18. Neuroticism environment. The innovation adoption rate with a population had reached the highest level of neuroticism trait.

In summary, while agreeableness and conscientiousness do not directly influence adoption behaviors, neuroticism significantly hinders adoption by reducing social engagement and increasing resistance to persuasion. These outcomes highlight the complex role of personality traits in shaping adoption behaviors and suggest that persuasive strategies targeting emotionally stable individuals may be more effective.

Examining the combined adoption rate curves across various scenarios reveals the impact of personality factors on innovation adoption. Each scenario reflects a unique combination of personality traits, and analyzing their combined effect highlights how individual variances influence the rate of adoption. The combined adoption rate curves (Figure 20) presented below demonstrates that peak adoption rates vary across scenarios, explaining how personality traits influence the rate at which individuals accept innovation.

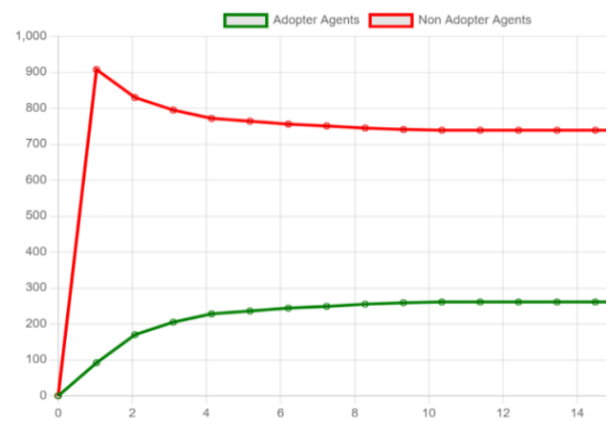


Figure 19. Conscientious, agreeableness, and neuroticism environment. Hypothesis testing that individual with high levels of conscientiousness and agreeableness would be more receptive to persuasion, whereas those with elevated neuroticism would be less.

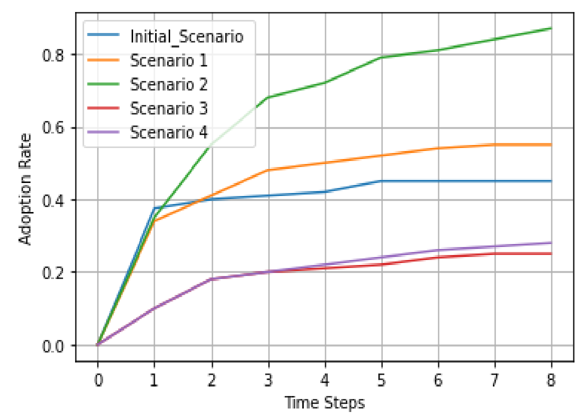


Figure 20. The adoption rate of innovations across scenarios

2.9. Conclusion

In this chapter, we have presented our proposed model. We described in detail the theories that were applied and how the Big Five personality model (OCEAN) was included into the Rogers innovation diffusion model. The model we have proposed takes into consideration several elements that are relevant to an innovation diffusion process.

Initially, we outlined the overall architecture of our model and clarified that individuals are reflected by agents, their profiles, personality types, and relationships are thoroughly detailed. Then, we exposed the individual decision-making process after explaining the motivations for choosing to merge the two models the OCEAN and Rogers model. In this regard, we illustrated our modeling of the individual (agents) social neighborhood; we have carefully highlighted the effect and impact of the psychological aspect “personality traits” on each individual's social connection, susceptibility to social influence, and peer persuasion.

Subsequently, we began incorporating the OCEAN model into Rogers' innovation diffusion theory. For that purpose, a novel model of innovation diffusion was put out, and three crucial components were identified innovation, agent, and innovation decision-making process. Innovation was used with its original definition as described by Rogers. Relative_advantage, complexity, compatibility, observability, and trialability are the five innovation characteristics; each feature was defined separately in the first section of this chapter. As previously mentioned, we use the concept of an agent to represent individual. Within the overall architecture, each agent is captured by a profile that includes the essential individual characteristics necessary for the dynamics of our diffusion process. Some of these characteristics pertain to the perception of innovation, known as perceived innovation characteristics, while the others define the agent's personality type.

Finally, considering that the decision to adopt or reject an innovation is not made instantly but progresses through a series of exchanges and updates to individual attributes, we conceptualized the innovation decision process as a sequence of phases. We identified four distinct phases: perception, communication, persuasion, and decision. At each step, a combination of individual characteristics is utilized to guide the process through these phases.

Notably, openness to new experience emerged as a critical factor; its impact can be significantly shown on the spirit individuals' innovativeness, and specifically in innovators and early adopter's categories. Scenarios featuring individuals in high-openness values have a higher adoption curve, indicating that innovations are adopted more quickly. People's willingness to take risks and explore new experiences increases the adoption process.

In contrast, high levels of neuroticism serve as a major barrier to adoption, peoples with high levels of neuroticism may suffer difficulty to social interactions, peer influence and persuasion, which make them to be more resistant to adopting innovation. By result, this lead to slower and more hesitant adoption process.

Extraverts, who are characterized for their sociability, energy, and enjoy the company of others, are more likely to emerge as opinion leaders, with a major impact on innovation adoption within their networks. Their personality type result in faster adoption rates since they endorse and share new discoveries with others.

The results of conscientiousness and agreeableness scenario had no substantial impact on adoption behavior, which is consistent with prior research. Conscientiousness and agreeableness alone do not determine an individual's susceptibility to persuasion. However, the neuroticism hypothesis was validated, since people with high neuroticism scores had limited social influence and weak communication skills, which hindered adoption by diminishing social engagement and raising resistance to persuasion. These findings indicate that persuasive methods aimed at emotionally stable persons may be more effective.

In the next chapter, we will demonstrate the application of our personality-driven innovation diffusion model using a real dataset, where the individuals' attributes are accurately regenerated through a combined model.

Chapter 3.
Use of the proposed model with automatic personality traits prediction for ChatGPT adoption

3.1 Introduction

Personality trait prediction and innovation dissemination are two interconnected domains that have made major theoretical advancements. Recent study investigates how individual differences, particularly those characterized by the Big Five personality traits, influence both the acceptance of innovations and the ability to forecast personality type.

This chapter aims to combine theoretical advances in personality trait prediction with practical applications of our model, demonstrating how predictive models can be utilized effectively in real-world settings particularly in the field of innovation diffusion. Personality-driven diffusion is the process by which personality factors impact the adoption and spread of innovations throughout social networks. This approach serves as crucial for understanding how innovations are spread and adopted by individuals and groups.

3.2. Significance of personality traits in innovation diffusion

Innovation diffusion and adoption are intricate processes affected by a number of factors, particularly the individual personality traits. Personality-driven diffusion performs an enormous effect in innovation diffusion contexts [103]. According to [104] it is personality that may explain and predict individual behaviors, such as the innovative work behavior. The term innovative work behavior includes all behaviors that contribute to the innovation process and can be regarded as part of this multidimensional entity.

The big five dimensions are strong indicators of individual behavior in a variety of contexts and life domains. Although traits are usually stable, they react dynamically to stimuli and may change over time.

Openness to new experience is frequently identified as a vital trait in innovation processes. Our initial implementation and research have revealed that openness is strongly linked to the generation of new product ideas and the exploration of novel opportunities [99], [105], [106]. This attribute benefits in the early phases of innovation by encouraging creativity and personal willingness.

Conscientiousness is another significant feature in innovation spread and acceptance, known as the organizer of the innovation process. It is related with organizational skills, diligence, and goal-oriented behaviors all of which are required for the successful diffusion process. However, conscientiousness might have contrasting consequences that depend on the context, such that highly conscientious individuals might favor organized, formal channels over informal communication. This contradiction highlights the varied function of conscientiousness across different innovation environments.

Extraversion, is the social driver of innovation diffusion. Extraverted people are more inclined to join in social interactions and to exchange information, thereby facilitating the spread of technologies. For example, extraversion is positively associated with the adoption of healthcare information in online communities because it encourages people to actively seek and share knowledge [7]. Furthermore, people with high extraversion are more susceptible to the effect of social networks and peer behavior [106]. This underscores the importance of extraversion in driving social diffusion of innovations.

Agreeableness is characterized by cooperation and empathy. Individuals with a high agreeableness score are more willing to participate in joint decision-making and collaborative efforts, which are critical for the successful adoption of innovations. This feature facilitates the acceptance and spread of collaborative innovations through cooperative interactions.

Neuroticism, that is marked by emotional instability and sensitivity to stress, performs a complex part in innovation adoption. Neuroticism can be viewed as a double-edged sword in terms of innovation acceptance. In general, neuroticism has a negative impact, especially when making risk-based decisions. Individuals who have high neuroticism might exhibit less risk-taking and more regret in cooperative decision-making circumstances. Otherwise high neuroticism can increase adoption rate. For example, in online healthcare groups, people with high neuroticism may be more inclined to adopt health-related innovations if they believe in them as a way to alleviate their concerns [7].

Understanding these qualities examines the explanations for why each of these characteristics is crucial in innovation diffusion field, helps explain disparities in innovation-related behaviors and technology adoption. For that reason researchers have developed and tested various models for personality traits prediction.

3.3. Computational models for personality trait prediction

Personality trait extraction is not a novel task; it is a well-established area of psychology [107]. Personality trait detection has become more important in both academic research and practical applications across a wide range of fields. It can be useful in a variety of domains including psychology, human resources, social media analysis, mental health diagnostics [108], political and voting intention, human-computer interaction [109], and also in marketing where it allows for the personalization of products based on the client' personality [110].

Traditional models for personality traits prediction have been primarily based on self-report techniques such as questionnaires, surveys and behavioral observations, which are used in psychology and psychometrics [108]. Overall, these models are often subjective and lack of generalizability across different populations and cultures, time-consuming, and have been shown to prone in bias particularly in terms of cultural and demographic characteristics [108].

However, with advancements in artificial intelligence, the automation of psychological assessments through digital traces like social media text is becoming more feasible and widely adopted. The analysis of social media data is one of the most effective strategies to forecast personality traits [111].

3.3.1. Natural language processing for personality analysis

Recent research in personality trait prediction has become increasingly concentrated on leveraging Machine Learning (ML) and Deep Learning (DL) approaches in combination with Natural Language Processing (NLP) in order to infer individual personality profiles from textual data. There is a great deal of interest in creating NLP models capable of autonomously identifying a person's personality traits for the examination of language use, which is an important indicator of personality characteristics [109].

NLP is a branch of artificial intelligence that encompasses a wide range of complex, sophisticated, and demanding language-related tasks, including summarization, machine translation, question answering, and sentiment analysis. In this context, models, methods, and algorithms are designed and implemented to address practical language comprehension issues. Its objective is to allow computers to understand human language words or sentences. It was created to facilitate user work and meet the need for natural language communication between the user and the machine [107], [110].

NLP is important in personality trait prediction as it enables the analysis and transformation of unstructured text, such as social media posts, written essays, or user feedback, into structured features that computational models can interpret. Linguistic patterns serve as a reference for psychological attributes in NLP applications, providing insight about individual's behavioral and emotional tendencies through their writing patterns, vocabulary choices, and communication style.

In this field, NLP methodologies are often divided into two categories: closed-vocabulary and open-vocabulary approaches.

- Closed-vocabulary approaches rely on pre-defined dictionaries or lexicons that divide words into psychologically relevant categories. LIWC (Linguistic Inquiry and Word Count) is a well-known example, which categorizes words into emotive processes (e.g., happy, cried, nervous) and social processes (e.g., friend, buddy, cousin, woman). The frequency of words in each category is then used to generate feature vectors that represent the author's language use in psychologically understandable terms.
- In contrast, open-vocabulary approaches extract features from text in a more flexible, data-driven manner. These features include n-grams, part-of-speech (POS) tags, emoticon use, text length, and semantic word embeddings such as Word2Vec and GloVe (Bitew et al., 2023). Open-vocabulary approaches are especially useful when analyzing user-generated content on social media, where the language is informal and highly diverse.

Once these features are extracted, they are used as input to ML and DL models that aim to identify patterns linked to personality traits. This preparation includes not only preprocessing steps like tokenization, lemmatization, and stop word removal, but also the extraction of relevant linguistic and psychological features. These structured representations enable computational models to learn patterns associated with specific personality traits, making NLP an essential layer of modern personality prediction systems architecture.

3.3.2. Literature review using Machine Learning

Machine learning (ML) techniques have played an important role in automating the prediction of personality traits by identifying patterns in linguistic and behavioral features extracted from textual data. These algorithms typically use hand-crafted features derived from NLP techniques, such as word frequencies, LIWC categories, n-gram statistics, part-of-speech tags, and semantic embedding.
ML models are trained to determine or predict personality scores, generally using existing models like the Big Five or Myers-Briggs Type Indicator (MBTI). These approaches in this domain can be divided into two categories: shallow (traditional) learning and ensemble learning strategies, as follows.

3.3.2.1. Shallow Machine Learning models

Shallow ML models which refer to traditional ML models that have a small number of layers in their architecture, include classical algorithms such as Support Vector Machines (SVM); a supervised learning algorithm considered as being extremely strong in classification, Naïve Bayes (NB) which is a probabilistic based classifier that is suitable for text data based on Bayes theorem, Decision Trees (DT) which creates trees with features threshold to divided data , and Regression models. These models are frequently used for simple classification and regression tasks; they are often favored for their easier interpretability and/or understandability. However, they may struggle with complex and high-dimensional data.

According to [109], various studies have investigated personality trait prediction with shallow machine learning (ML) approaches, demonstrating the effectiveness of these algorithms. For example, [112] used SVM and Multinomial Naive Bayes (MNB) to analyze Twitter data, revealing a substantial relationship between online behavior and personality traits. [113] increased the data scope to include Facebook, expert knowledge for deeper insights, and used NB classifiers to predict personality from Twitter datasets. In [114] Word embeddings and supervised learning models have been used to extract personality traits from Twitter posts.

In the field of unsupervised learning, [115] used K-means clustering on MBTI-labeled data to classify users according to linguistic patterns. The work reported in [116] presented a novel classifier that uses dialogue-based features to predict the personality traits of non-playable characters in visual novels. In the meantime, a regression model was created by [117] with the goal of reducing dimensionality in personality feature values. The scope of some other approaches is beyond text: [118] used decision tree models to determine personality traits and evaluate students' academic performance. [119] used word embeddings to extract user behavior and infer personality from tweets, implementing a variety of machine learning models on the Apache Spark platform. Lastly, [120] examined the interdependencies across personality traits by analyzing data dimensions in digital platforms, providing a trait-prediction framework based on user behavior.

3.3.2.2. Ensemble Learning Methods for personality trait prediction

Ensemble learning methods combine multiple models to improve prediction accuracy and generalization, particularly in scenarios with complicated feature relationships or imbalanced data. These methods have become popular for predicting personality traits on a variety of platforms.

For instance, to enhance classification performance, [121] suggested a soft voting ensemble that makes use of several Support Vector Machine (SVM) kernels. [122] combined Linguistic Inquiry and Word Count (LIWC) indicators with Term Frequency–Inverse Document Frequency (TF-IDF) features at the character and word levels.

[123] demonstrated the usefulness of bagging algorithms, especially for predicting extraversion, conscientiousness, and openness. By combining Word2Vec embeddings with Light Gradient Boosting Machine (LightGBM), an effective yet interpretable machine learning ensemble technique, [124] achieved improved classification. Finally, [125] discovered that in several types of personality prediction tasks, combining K-means clustering with Extreme Gradient Boosting (XGBoost) outperformed traditional Naive Bayes classifiers.

3.3.3. Literature review using Deep Learning

Deep learning (DL), a subfield of machine learning (ML), is suitable for modeling complicated and high-dimensional data like natural language. Multi-layered neural networks enable DL models to extract abstract features and learn intricate patterns needed for personality trait prediction from textual, audio, or behavioral data. These models often need huge datasets and significant computer resources, nevertheless they frequently outperform classical machine learning models in terms of accuracy and generalization.

In this regard, two main families of deep learning models have arisen in the literature: sequential deep learning models and transformer-based models [109]. Each kind has unique architectural strengths that make it ideal for NLP applications, notably recognizing user-generated information like social media text. The following paragraphs explain how each kind works and provide an overview of the most relevant studies which depend on these models.

3.3.3.1. Sequential deep learning models

These models are specifically designed to process input data where word position or sequence as well as time-related connections between sequence elements are important. The Recurrent Neural Network (RNN) is the simplest basic model in this category. RNNs are very effective in natural language processing, speech recognition, time series prediction, and other applications that need sequential or temporal data. RNNs' main feature is the utilization of recurrent connections, which allow information to be transmitted from one step to the next [126]. The network establishes recurrent connections by incorporating loops that allow the output of the previous time step to be used as input for the current time step. However, RNNs frequently suffer with long-term dependencies in the input sequence.

To address this, the Long Short-Term Memory (LSTM) architecture was devised, which includes memory cells and gating mechanisms that control the flow of information and enable the model to retain essential elements over longer sequences. The Gated Recurrent Unit (GRU) is a more computationally efficient version of LSTM that uses a simpler mechanism inside compared to LSTM, while preserving comparable performance.

Additionally, Bidirectional LSTM (Bi-LSTM) networks improve contextual interpretation by processing data in both forward and backward directions. This architecture is made up of two LSTM layers: one processes the sequence in the forward direction (going from the first time step to the last) and the other in the backward direction (from the last time step to the first) [127], [128], [129]. By combining information from both directions, Bi-LSTM models may capture a larger context and improve their capacity to represent temporal relationships in sequential data. Convolutional Neural Networks (CNNs), which were originally created for image recognition, have also been used in personality prediction tasks to extract local features from text sequences. They are frequently combined with LSTM layers for improved performance.

In the literature, [130] compared CNNs to RNN-based architectures and discovered that sequential models are superior at capturing user writing patterns. [131] used pre-trained Word2Vec embeddings along with LSTM layers to predict personality attributes on social media platforms. [132] used CNNs to interpret multimodal data (text and facial expression) for detecting learner personality types, proving the models' adaptability beyond textual analysis.

3.3.3.2. Transformer-based deep learning models

Transformer-based deep learning models have considerably improved personality trait prediction by allowing for the extraction of contextual and semantic elements from text. Transformers, unlike sequential models, use self-attention techniques to capture long-range dependencies, making them particularly good in understanding complicated language patterns. One of the most popular transformer architectures is BERT (Bidirectional Encoder Representations from Transformers), which processes text in both directions to generate rich contextualized embeddings. DistilBERT, a distilled and lightweight version of BERT, provides faster performance with the same accuracy. SBERT (Sentence-BERT) improves BERT to provide sentence-level embeddings optimized for similarity and clustering activities, which are useful in personality evaluation. GPT (Generative Pre-trained Transformer) is a unidirectional model that specializes in text generation but may also be used for classification problems.

In addition of these, a number of additional transformer variants have been used in recent research. RoBERTa (Robustly Optimized BERT Approach) is a pre-trained language model that aims to improve BERT model performance by optimizing training procedures [133]. RoBERTa trains on a larger dataset, considerably improving the model's language representation capabilities [134]. Unlike BERT, RoBERTa eliminates the Next Sentence Prediction task and keeps only the training target based on the Masked Language Model [134]. RoBERTa, does not predict sentence-pair relationships like BERT, it is entirely focused on learning word meanings from context through the prediction of masked tokens. This adjustment does not degrade model performance, but rather reduces unnecessary constraints, simplifies training, and shifts the model's focus to deep word-level understanding, ultimately enhancing task performance [134].

ALBERT (A Lite BERT) and SBERT (Sentence-BERT) have all been successfully used in personality detection. These transformer models have produced competitive results when simulating the complex connections between language patterns and the Big Five personality traits.

3.3.4. Strengths and limitations of personality prediction models

ML and DL models have different strengths and weaknesses when it comes to detecting personality traits. Traditional machine learning models are favored for their interpretability and efficiency on small datasets, but they frequently fail to grasp deeper semantic and contextual complexities. Ensemble approaches improve generalization and avoid overfitting, but they are less effective with highly contextual data. Deep learning models excel at learning complicated patterns and managing long-term connections, but they require enormous datasets and significant computer resources. Transformer-based models provide sophisticated contextual understanding and high performance with complex language, but they are difficult to interpret and require a large amount of labeled data and processing capacity. Finally, the model choice should be consistent with the data properties, trait complexity, and computational resources [109]. Hybrid model that combine interpretability, feature learning, and contextual comprehension may provide the most successful solutions, as we will see in the following sections.

3.4. Application of the proposed model on ChatGPT-related social media data

Simulation using real-world datasets is a popular approach in various sectors. The integration of real-world datasets in simulation creates a more realistic and diverse environment for training and testing models, potentially improving performance and generalization. Real-world datasets can also help to close the simulation-to-reality gap, which can be a substantial difficulty in simulation [135], [136]. One technique to use real-world datasets in simulation is to validate and refine simulation models [137], [138]. By comparing simulated data to real-world data, researchers and practitioners can identify areas where simulation models need to be improved or updated.

This section offers a critical contribution by empirically applying the personality-driven innovation diffusion model to a real-world dataset of ChatGPT-related tweets. The basic idea is to fill the gap between theoretical modeling and real-world user behavior by focusing the diffusion process on experimentally predicted psychological features. To do this, Twitter users' personality traits are predicted using a combination of NLP, ML, and DL models based on the commonly accepted Big Five personality framework. The perceived innovation qualities are then analyzed and regenerated using sigmoid, mean, and weighted functions. These characteristics are then included into an agent-based simulation model that regulates the innovation adoption process, resulting in a more nuanced and personalized portrayal of individual decision-making and social influence mechanisms.

This study enhances the theoretical framework of personality prediction by moving its application beyond static profiling to dynamic behavioral modeling. It demonstrates the manner in which psychological features extracted from publicly available digital traces may assist to lead simulations of real-world phenomena like innovation adoption. This marks a significant methodological transition from theories, resulting in improving the realism, variability, and interpretability of diffusion dynamics.

Furthermore, this study presents a new interdisciplinary strategy that integrates innovation diffusion theory, personality prediction, and social media analytics. By combining these elements, it is possible to investigate how personality factors impact on the perception of innovation attributes—like relative_advantage, compatibility, uncertainty, and influence, which in turn impact the adoption rate. By using real-world behavioral data and a theoretically grounded diffusion model, this application provides new insights into the micro-level psychological elements that drive macro-level dissemination patterns. It also brings up new opportunities for developing more targeted and personalized innovation models in both academic and practical settings.

3.4.1. Dataset overview

The original dataset used for this study includes 39,055 ChatGPT-related tweets, each with corresponding user metadata such as username, user description, follower count, hashtag... etc. (as shown in Figure 21; a sample of the dataset displaying selected columns along with user tweets and metadata, since it is not feasible to present the complete dataset in its entirety). The dataset is publically available in [139] and was chosen for its high relevance to the study's focus on ChatGPT adoption.

In addition to its relevance, the chosen dataset has been extensively used in the scientific community. As of July 2025, it had more than 21,900 views and 2,480 downloads, with an average engagement rate of 0.113 downloads per view. The majority of users reported using the dataset primarily for research and learning. While no fine-tuning or direct application actions have been noted, the dataset has been described as well-maintained and often visited in the recent 30 days. This strengthens the dataset's usability and relevance for examining ChatGPT adoption behaviors using a personality-based diffusion model.

Along with tweet content, dataset contains detailed user information that allows for the prediction of personality attributes needed for empirical application of the recommended personality-driven innovation adoption model.

However, it is critical to recognize any potential biases in the dataset. Twitter users are not a truly reflective of the broader population; earlier studies have revealed that Twitter platform's user base is younger and more male [140], [141]. This demographic inconsistency may have an impact on the findings' generalizability, particularly in terms of adoption behaviors that range by age and gender group. As a result, caution is recommended when projecting these findings to larger or more demographically diverse groups.

3.4.2. Pre-processing of dataset for model application

The dataset described above serves as the foundation for predicting individual personality traits based on their tweets and associated user metadata. Prior to applying feature extraction and selection algorithms, the dataset undergoes preprocessing procedures. Data preprocessing involves transforming row data into a format suitable for analysis, processing, and implementation. The primary objectives of data preprocessing include enhancing data quality, eliminating noise, and improving data comprehensibility and reusability for subsequent tasks.

Filtering. The initial step involved removing non-ChatGPT-related tweets, which reduced the dataset from 39,055 to 38,939 users. This filtering process was essential to maintain research focus exclusively on ChatGPT-related content, thereby enhancing the relevance and accuracy of subsequent analyses.

Text cleaning. Both user descriptions and tweets underwent thorough cleaning to prepare them for prediction algorithms. This process involved removing non-standard characters, user mentions, emojis, URLs, and special symbols that could introduce noise into the analysis. The cleaned text was then tokenized by splitting it into individual units (tokens or words) using whitespace and punctuation delimiters. Stop words—common words such as "the," "is," and "and" that typically carry minimal semantic meaning—were subsequently removed from the tokenized text to reduce noise and emphasize more meaningful content.

Text normalization. To ensure consistency in text representation, all text was converted to lowercase, and word variations were standardized to their base forms through lemmatization. Unlike stemming, which applies heuristic rules to truncate words, lemmatization employs vocabulary and morphological analysis to obtain the correct dictionary form (lemma) of words. This approach proves particularly valuable for sentiment analysis, personality assessment, and behavioral profiling tasks [109].

Metadata normalization. User metadata, including the number of followers, followings, and tweets, underwent normalization to convert all variables to a consistent scale. This normalization process was crucial for ensuring data integrity and enabling comparability across different users, while minimizing potential biases and variability arising from inconsistent data scales.

These preprocessing steps collectively ensured that the dataset was clean, consistent, and optimally formatted for feature extraction and personality prediction modeling.

3.4.3. Personality prediction model selection and development

As previously mentioned, the choice of predictive model must align with the data properties, trait complexity, and available computational resources. Given that our dataset contains both textual data (tweets and user descriptions) and structured data (user metadata), hybrid models that effectively combine interpretability, feature learning, and contextual comprehension offer the most promising solutions for personality prediction tasks.

To achieve accurate and reliable predictions of users' Big Five personality traits, we developed several hybrid compositional models that integrate deep learning architectures with ensemble methods:

- **BERT-RF**: Combining Bidirectional Encoder Representations from Transformers with Random Forest
- **LSTM-RF**: Integrating Long Short-Term Memory networks with Random Forest
- **BiLSTM-RF**: Pairing Bidirectional LSTM networks with Random Forest
- **RoBERTa-RF**: Merging Robustly Optimized BERT Pretraining Approach with Random Forest.

User-name	Text	User-description	User-followers	User-friends
PharmaTechnologyTrends	*ChatGPT is a truly mind-blowing tool and playing around with it will definitely send you down a rabbit hole, but it can also actually help you with your marketing and content creation. Here are five ways to leverage ChatGPT in your workflow. #ChatGPT... https://t.co/ch6TOuuDm4*	*Latest News and Trends in Pharmaceutical Industry*	*264*	*4333*
TrustworthyInfluencer	*This is how #ChatGPT will change forever any form of knowledge 1 picture 2 OCR and copy 3 paste 4 enjoy #GPT3 #AI #Algorithms #MachineLearning #Learning #ML @OpenAI #AI #ArtificialIntelligence #techforgood #flutter #NLP #BigData #technology https://t.co/lufdNMBJpP*	*Hi, I am a marketing, business, investment & technology consultant. My company (ORCA: https://t.co/otXUkisexW) focuses on consulting & solutions development. Thank you.*	*20*	*58*
Mr. Joe Nava	*The future is here. See my demo of @OpenAI's #ChatGPT for #Educators. What's mind-blowing is that it will only get better. https://t.co/OfSOIdJgZJ*	*Math Teacher, Proud Domer, Ignatian Educated Educator, Catholic School Advocate, Recovering Perfectionist, Aspiring Good-Enoughist #GrowthMindset #AMDG*	*121*	*170*
Sophia Ahmed	*Excellent examples by Saba of using #chatgpt in creating summaries (Iqbal's work) & by creating blurb on her own books & â¬†ï¸ sales Asking the bot the right questions was key. Great insights Saba. #earnwithchatgpt*	*Lead Mentor @aug_mentor Consulting & youth-led initiatives @khudkaar @sciencefuse @sukhan_official @salamdocufilm Threads on books, spaces & podcasts*	*6410*	*3607*
Abhas Tandon	*These opinions are not mine. The above criticism of "ChatGPT" was generated using #ChatGPT ðŸ˜… Prompt: "Let's assume you are a technology author who is critical of ChatGPT. Write a hypothetical tweet thread to show that? "*	*Yet another Software Engineer. #JavaScript #nodejs #python #html #css (tweets== bookmarks/note to self/complains)*	*3549*	*1318*

Figure 21. Sample of ChatGPT-related tweets dataset.

These combined architectures use the contextual understanding skills of transformer and recurrent neural network models to analyze textual information, while Random Forest's ensemble learning technique successfully addresses both extracted deep features and structured metadata.

3.4.3.1. Evaluation Metrics

Since we do not have access to a real personality dataset with ground truth labels, traditional supervised learning evaluation metrics such as F1-score, precision, recall, and accuracy cannot be applied. Therefore, to identify the most reliable and robust hybrid model for personality trait prediction, we employed three alternative evaluation metrics that assess model performance without requiring labeled data:

• **Variance**: Measuring the consistency of predictions across different data samples to evaluate model stability.

• **Range**: Evaluating the spread and distribution of predicted values to assess the model's ability to capture personality trait diversity.

• **Predictive stability**: Assessing the model's ability to maintain consistent performance across various experimental conditions and data subsets.

3.4.3.2. Model performance

The BERT_RF model, as presented in (Table 1), consistently outperforms other combined models such as LSTM_RF, BiLSTM_RF, and RoBERTa_RF in terms of maintaining a higher variance and capturing a broader range of personality traits, particularly Openness and Conscientiousness. Furthermore, BERT-RF displays near-perfect stability over multiple runs, which makes it essential for accurate personality prediction and promoting reliable and consistent predictions.

3.4.4. Personality traits extracted using BERT-RF model

Our hybrid architecture integrates BERT's linguistic processing capabilities with Random Forest classification to predict personality traits from Twitter data. BERT, a pre-trained transformer model, converts preprocessed tweet text into contextual embeddings that capture semantic relationships and linguistic difficulties within a high-dimensional vector space. Concurrently, User metadata is preprocessed to normalize numerical variables and encode categorical attributes in a structured feature vector. This dual-component model can take advantage of each's strengths to make accurate personality characteristic extraction. The integrated workflow can be formalized as:

$$P_i = \ Random\ Forest\ \left(\left[BERT\ \left(Tokenize(T_i);\ Normilaze(M_i)\right)\right]\right) \tag{7}$$

Textual features (*Ti*) are processed through BERT, whereas metadata features (*Mi*) are normalized and encoded. The processed inputs are concatenated and passed to the Random Forest model to extract personality traits values. (*Pi*) = [pO,pC,pE,pA,pN], reflecting predicted scores across the Big Five personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

The enhanced dataset thus includes the original ChatGPT-related tweets, user demographic and behavioral metadata, and the derived personality trait scores, resulting in a full input structure for subsequent personality-driven innovation diffusion analysis.

3.4.5. Perceived innovation attributes processing

This stage aims to generate realistic perceived innovation attribute values using the extracted personality trait scores. We rely on the resulting personality characteristics to compute perceived innovation dimensions such as relative_advantage, acceptability, uncertainty, compatibility, influence, and innovativeness (shown in Figure 5).

- ***Relative_advantage.*** For that attribute we used a weighted function to ensure that the contributions of innovation' relative_advantage and openness are balanced and reflective of their actual significance in determining the overall individual' relative_advantage score.

$$Relative - advantage = min\,(10, max\,(0, (Relative\_advantage\ \times\ weight_{Relative-advantage}) + (Openness \times 10 \times\ weight_{Openness}))) \quad (8)$$

- ***Acceptability.*** The used formula calculates the acceptability score using the mean of extraversion and agreeableness values, adding a small random noise ϵ uniformly distributed in the interval [-0.05, 0.05] that introduces slight variability, reflecting the nuanced nature of real-world data.

$$Acceptability = mean(Extraversion, Agreeableness) + \epsilon \quad (9)$$

- ***Uncertainty.*** The selected sigmoid formula determines that agent's uncertainty is mainly driven up by neuroticism and down by conscientiousness, with a fixed offset determining the general baseline, and small external factors adding randomness. By using the sigmoid function the final value is always between 0 and 1.

$$Uncertainty = \sigma(\alpha \cdot Neuroticism - \beta \cdot Conscientious + offset + external\_factors) \quad (10)$$

Where :

- ***σ(x)***= $\frac{1}{1+e^{-x}}$, is the sigmoid function.

- α is the weight for neuroticism, higher neuroticism increases the input, making the agent more uncertain.
- Conscientiousness weighted by **β** but subtracted, higher conscientiousness reduces the input, making the agent less uncertain.
- ***Offset*** is a constant value applied to the combined personality characteristic input. In this formula, the offset is set to a positive fixed value (+0.5) to guarantee that agents start with an increased degree of uncertainty, which can later be reduced through communication and other interactions. Because it is fixed, the offset affects all agents identically and remains constant throughout the simulation, acting as a baseline bias before personality traits and random environmental factors are addressed.
- ***External factors*** are a random value uniformly distributed between 0 and 0.2, added to introduce slight variability. The curve below (Figure 22) depicts the typical behavior of the sigmoid function.

- ***Compatibility.*** The compatibility value is computed using a weighted function where each relevant trait is multiplied by its corresponding weight, which determines the strength of that trait's contribution to overall compatibility.

The max (0, …) part prevents the result from falling below zero, ensuring that compatibility values remain non-negative even when some weights are negative or low trait scores. Similarly, the min (…, 1) component caps the result at 1, preventing compatibility values from exceeding the maximum threshold, as follows:

$$\text{Compatibility} = \min\Big(\max\Big(0, \big(\text{weight}_{\text{Openness}} \cdot \text{Openness} + \text{weight}_{\text{Conscientiousness}} \cdot \text{Conscientiousness} + \text{weight}_{\text{Agreeableness}} \cdot \text{Agreeableness}\big)\Big), 1\Big) \quad (11)$$

- ***Influence.*** The following formula calculates an agent's influence score using three personality traits. Neuroticism is assigned a negative weight because higher neuroticism typically diminishes one's influence in social context. Agreeableness receives a positive weight, as individuals with high agreeableness tend to be more persuasive and collaborative.

Conscientiousness also with a positive weight, since conscientious people are often perceived as reliable influencers. (Figure 23) illustrates the combined effect of these aforementioned traits.

$$\text{Influence} = \min(\max(0, (\text{weight}_{Neuroticism} \cdot \text{Neuroticism} + \text{weight}_{Agreealeness} \cdot \text{Agreeableness} + \text{weight}_{Conscientious} \cdot \text{Conscientiousness} +)), 1) \quad (12)$$

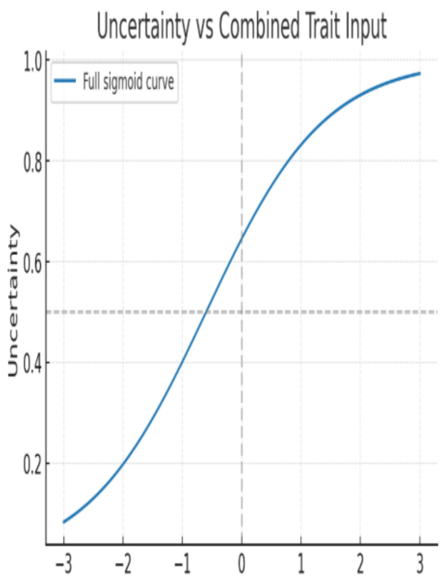


Figure 22. Sigmoid function curve

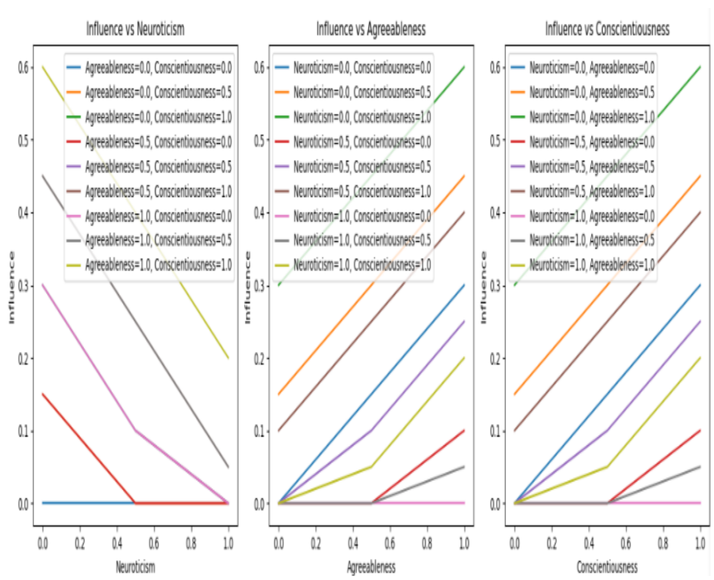


Figure 23. Influence curve derived from neuroticism, agreeableness, and conscientiousness traits

- ***Innovativeness.*** Innovativeness value reflects the weighted contribution of the openness trait and incorporates a minor random factor, to realistic fluctuations.

$$\text{Innovativeness} = \min(\max(0, (\text{weight}_{Openness} \cdot \text{Openness} + \text{random\_factor})), 1) \quad (13)$$

3.4.6. Experimental results and analysis of the personality-driven model for ChatGPT adoption.

This section outlines how we applied our personality-based innovation diffusion model to predict ChatGPT adoption patterns among users. As model input, we combined the ChatGPT-related tweets dataset with the regenerated perceived innovation traits and predicted OCEAN values (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). By merging these empirical data sources, we examined how various personality dimensions influence innovation adoption processes.

Variance of Personality Traits:	**BERT-RF**	**LSTM_RF**	**BiLSTM_RF**	**RoBERTa_RF**
Openness	0.014574	0.014524	0.037718	0.070848
Conscientiousness	0.013968	0.014960	0.045071	0.067071
Extraversion	0.014474	0.014423	0.037827	0.009494
Agreeableness	0.013609	0.015288	0.039206	0.010071
Neuroticism	0.013630	0.014934	0.009764	0.009936
Range of Personality Traits (Max - Min):				
Openness	0.871856	0.894430	0.955645	0.992629
Conscientiousness	0.970149	0.907778	0.970631	0.982802
Extraversion	0.844633	0.939326	0.967033	0.500000
Agreeableness	0.810405	0.971067	0.934661	0.728520
Neuroticism	0.844237	0.866604	0.500000	0.500000
Predictive Stability Across Multiple Runs:				
Openness	0.975363	0.976520	0.990528	0.999783
Conscientiousness	0.975470	0.976543	0.990560	0.999791
Extraversion	0.975519	0.976571	0.990627	0.999779
Agreeableness	0.975745	0.976332	0.990677	0.999789
Neuroticism	0.975640	0.976618	0.990544	0.999798

Table 1. Predictive Model Performance: Variance, Range, and Stability.

Our methodology included the aforementioned four main phases of our proposed individual decision-making model perception, communication, persuasion, and decision (see Section 2.6. The proposed innovation decision-making process). We assessed users' adoption rate of innovations through their personality profiles by measuring compatibility, acceptability, uncertainty levels, and social influence values. We then examined how these elements shape user adoption behaviors and decisions across time periods, ultimately categorizing users into adoption states (Adopter or Non-Adopter).

This implementation generated a predicted adoption trajectory curve for ChatGPT (Figure 24), offering valuable understanding of how personality traits, perceived innovation attributes, social dynamics, and peer influence collectively drive adoption behavior patterns.

The simulation begins by initializing each user-agent with personality traits obtained from the ChatGPT-tweets dataset and a link to shared innovation variables such as relative_advantage, complexity, and so on. The secondary values denoted by perceived innovation features like acceptability, influence, and uncertainty take then primary values that are derived from their personality traits. All agents are randomly arranged in a grid, where they interact with their neighbors. During each simulation step, certain characteristics values are updated based on the model process, and each agent decides whether to adopt the innovation based on the calculated adoption probability, which is determined by all of the aforementioned model factors. The entire adoption curve is then represented by collecting the number of adopters over time.

The simulation generated a ChatGPT adoption rate curve follows a pattern similar to the S-curve commonly seen in innovation diffusion models. Initially, adoption evolves slowly, showing the cautious behavior of the majority of agents and the limited influence of innovators. As time passes, adoption increases dramatically as early adopters start to influence others agents, resulting in the rapid spread of the innovation across the network. Eventually, the curve stabilizes, signifying saturation, in which nearly all agents who are more likely to adopt have done so.

During the initial phase, early adopters with specific personality attributes (such as high Openness, innovativeness, and in some cases high extraversion) rapidly accepted ChatGPT. Understanding these characteristics can assist target marketing efforts and initial implementation strategies aimed at attract this category.

As the innovation obtains awareness and credibility, its adoption rate accelerates, owing to social interaction and influence impact. Communication and word-of-mouth raise innovation relative_advantage, reduces uncertainty value, and ultimately increases the adoption rate. This stage corresponds to the steepest phase of the S-curve. Social networks and providing positive user experiences can significantly increase adoption rate during this stage.

Finally, the adoption rate curve becomes saturated, indicating that the majority of potential users have already used ChatGPT. This pattern demonstrates the dynamic interaction of individual personality traits, perceived innovation characteristics, and social influences in shaping the adoption rate. Strategies should focus on maintaining user engagement and looking into new features or enhancements to keep users interested.

The simulation results demonstrate how individual adoption decisions emerge from the combination of personality traits and innovation attributes via the four key behavioral mechanisms perception, communication, persuasion, and decision. Together, these mechanisms produce a classical S-curve. Furthermore, the findings confirm that including real values for personality-driven qualities enables the model to effectively reflect the diverse adoption behavior observed in real-world social systems.

Despite that our model converges to almost 100% adoption unlike the randomly generated simulation, this outcome should be interpreted in the context of how personality traits are included. For instance, agents with high neuroticism typically adopt more slowly because they are less receptive to uncertainty and have less interpersonal connections. In the current setup, these agents, however, have a retain probability of being adopter by creating permanent resistance, that can lead to adoption in the long run.

Further, misclassified adopters are agents whose adoption decisions depart from predicted outcomes based on their personality profiles and estimated influence factors. For example, agents who have a high level of neuroticism or low openness occasionally adopted early, but some with high extraversion did not adopt completely. These scenarios are not fundamental but highlight the complexities and heterogeneity of human behavior. Furthermore, random variables in agent-based simulation and social influence can contribute to such results. Addressing these misclassifications is significant since it demonstrates the model's realism in simulation and probabilistic human decisions. Future improvements could include more external factors to eliminate this variation.

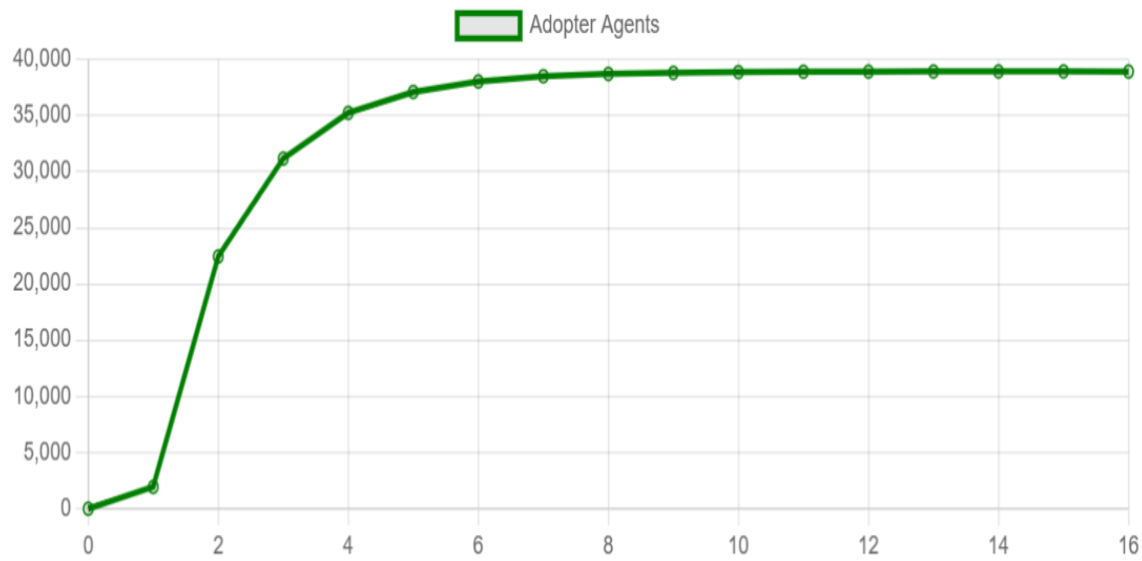


Figure 24. Personality-driven ChatGPT adoption curve.

3.4.7. Discussion of results

The experimental results confirm that integrating personality traits into the diffusion process significantly improves the explanatory power of innovation adoption modeling. The emergence of an S-shaped adoption curve indicates that the proposed model successfully reproduces the fundamental dynamics described in Rogers' diffusion theory while incorporating individual heterogeneity. Unlike classical diffusion models that assume homogeneous adopter behavior, the proposed framework demonstrates that adoption speed and timing vary substantially according to psychological profiles.

The early adoption behavior observed among agents with high Openness and innovativeness is consistent with psychological and diffusion literature, which identifies openness as a key driver of curiosity, experimentation, and acceptance of novel technologies. This finding validates the theoretical assumption that personality traits directly influence innovation perception and adoption readiness. Similarly, the faster diffusion phase driven by socially active agents, particularly those with higher Extraversion and Agreeableness, highlights the critical role of interpersonal communication and social influence in accelerating adoption across the network.

The reduction of perceived uncertainty and the increase of relative advantage during the persuasion and communication phases further demonstrate the dynamic interaction between individual cognition and collective social processes. As more agents adopt ChatGPT and share positive experiences, the innovation becomes more credible and attractive, which reinforces adoption behavior. This result supports the hypothesis that perceived innovation attributes should not be treated as static parameters, but rather as evolving variables shaped by social interactions.

The convergence of the model toward a high adoption rate reflects the strong influence of cumulative social pressure and network effects. While this behavior is consistent with viral diffusion patterns commonly observed in digital platforms, it also reveals a limitation related to long-term resistance modeling. The results suggest that even agents with high Neuroticism or low Openness may eventually adopt due to persistent exposure and repeated social influence. This highlights the importance of introducing stronger resistance mechanisms or external constraints in future model extensions to better reflect real-world non-adopter populations.

The presence of misclassified adopters further emphasizes the stochastic and non-deterministic nature of human behavior. These deviations demonstrate that adoption decisions cannot be explained solely by personality traits, but are also affected by randomness, contextual factors, and unpredictable social interactions. Rather than being a weakness, this variability enhances the realism of the simulation by reflecting the uncertainty and diversity observed in real social systems.

Overall, the experimental results demonstrate that the proposed personality-driven diffusion model captures both macro-level diffusion patterns and micro-level behavioral diversity. This dual capability represents a significant improvement over traditional diffusion approaches and confirms the relevance of combining psychological modeling, machine learning-based personality prediction, and agent-based simulation for studying innovation adoption in online social networks.

3.5. Conclusion

During the preliminary simulation presented in the previous chapter, we implemented the personality-driven innovation adoption model using randomly generated Big Five personality values assigned to each agent. This approach enabled us to assess the diffusion processes within a controlled simulation framework. In this chapter, however, we move beyond this synthetic approach by presenting the ML, DL, and NLP techniques employed to derive personality traits from real user data, then we illustrated the experimental results and analysis of the personality-driven ChatGPT adoption simulation. The personality predictive frameworks facilitate the incorporation of realistic personality profiles and model factors into our adoption model.

General Conclusion

1. Conclusion

This thesis successfully designed and validated a comprehensive personality-driven diffusion model, filling significant gaps in traditional innovation diffusion theory. This study offers new perspectives about how individual psychological features influence the adoption and diffusion of innovations by combining Rogers' diffusion of innovation framework with the Big Five personality model via agent-based simulation.

2. Key achievements

The research achieved its aforementioned fundamental objectives. **Theoretically**, we have developed a new framework that bridges the gap between classical diffusion theory and current understanding of individual psychological characteristics. The personality-driven innovation diffusion model shows how the Big Five qualities (openness, conscientiousness, extraversion, agreeableness, and neuroticism) influence innovation perception, adoption and decision-making behaviors, and social interactions throughout the diffusion process. This is an important advancement further from traditional models that view adopters as homogeneous groups, demonstrating the complex interplay of personality traits and innovation characteristics that defines real-world adoption behaviors.

Methodologically, the thesis presents an effective two-phase simulation approach which incorporates theoretical rigor and empirical validation. The agent-based simulation framework properly reflects the heterogeneity of individual decision-making processes while preserving the emergent features that result in the classical S-shaped diffusion curve. The use of machine learning techniques, notably the hybrid BERT-Random Forest model for personality prediction based on social media data, highlights how computational methods can connect theoretical models to real-world behavioral data. This methodological innovation opens up novel opportunities for testing diffusion theories through large-scale digital traces of human behavior.

Empirically, the ChatGPT case study demonstrated the model's practical applicability and predictive ability. The investigation of ChatGPT adoption using Twitter data demonstrates how personality-driven factors influence the rapid dissemination of AI technology in digital society.

The findings show that individual psychological qualities have a major impact on not only adoption timing, but also the mechanisms by which innovations diffuse via social networks. This case study supports the theoretical framework by demonstrating its relevance to current technological events.

3. Implications

The study found that personality factors serve as important moderators in the innovation diffusion process, influencing several phases from initial awareness to final decision. The model demonstrates how people with different personality profiles perceive innovation qualities differently, respond differently to social influence, and exhibit distinct communication behaviors that impact diffusion outcomes. This observation challenges the traditional hypothesis of homogeneous adopter categories, implying that successful diffusion approaches must take into consideration psychological variability among target social system.

Furthermore, the thesis provides evidence that classic static measurement of innovation traits fails to account for the dynamic nature of adoption. The personality-driven diffusion model demonstrates how psychological dimensions influence the evolution of perceived innovation characteristics over time, resulting in a more nuanced view of adoption decision-making that is more accurate to real-world complexity.

The findings have, further, important practical implications for innovation managers, policymakers, and technologists. This present personality-driven approach delivers actionable insights for developing targeted adoption techniques based on the psychological profiles. Organizations can use these findings to create more successful communication strategies, identify key influencers based on personality attributes, and enhance the adoption rate across varied populations. The model provides policymakers with a comprehensive tool for forecasting and managing societal adoption of novels, especially in situations where recognizing individual differences is critical for successful implementation. The approach can be beneficial to inform evidence-based policies that plan innovation diffusion activities while taking into account population heterogeneity in personality traits.

4. Limitations

Despite the contributions of this work, several limitations should be acknowledged. First, the personality prediction process relies on social media textual data, which may not fully reflect users' real psychological profiles. Although the hybrid BERT–Random Forest model provides promising results, personality inference from digital traces remains an indirect approximation and can be affected by noisy content, informal language, sarcasm, or platform-specific communication behaviors.

Second, the study focuses exclusively on the Big Five personality framework. While this model is widely accepted and validated, it does not capture all psychological dimensions that may influence innovation adoption, such as motivation, values, risk perception, or emotional states. As a result, some aspects of individual decision-making behavior may not be fully represented in the current model.

Third, the agent-based simulation relies on predefined assumptions and parameter settings to model social interactions and adoption behavior. Although these assumptions are theoretically grounded, they simplify real-world complexity. Human behavior is influenced by many external factors such as economic constraints, media influence, and sudden technological changes, which are not explicitly modeled in the current framework.

Finally, the social network structure in the simulation is considered relatively static during the diffusion process. In reality, online networks are dynamic and continuously evolving, with users forming and dissolving connections over time. This simplification may limit the model's ability to fully capture real-world diffusion dynamics.

5. Future research directions and perspectives

In future studies, the incorporation of other psychological frameworks outside of the Big Five approach could potentially be addressed. The theory of cultural dimensions could be applied to investigate how personality traits interact with regional and national cultural differences to affect diffusion patterns in various societies. Another interesting area for theoretical advancement is temporal dynamics. Future models should look into how personality and innovation interactions change over the life cycle of an innovation, and whether the importance of particular traits shifts as innovations grow and start to gain popularity.

Additionally, the accuracy of personality assessment from digital traces could be greatly increased by the creation of multi-modal personality prediction models that incorporate textual data with behavioral, visual, and network elements. When combined with the current personality-driven diffusion model, advanced deep learning architectures—such as transformer-based models created especially for personality prediction—could capture deeper linguistic patterns predictive of personality traits, which would undoubtedly be a significant advancement.

Currently, some researches work on dynamic social networks and co-evolution models — where both network structure and diffusion processes change over time—. Fortunately, rather than emphasizing dynamics driven by personality, the majority of them concentrate on behavioral or structural norms. Future studies that incorporate personality qualities into dynamic network modeling may be valuable and offer more profound understandings of how social structures and the diffusion of innovation co-evolve.

As a practical application, future studies could investigate personality-driven systems that combine real-time diffusion monitoring, tailored innovation design, and policy simulation in order to improve adoption prediction, customization, and societal impact assessment

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Publications related to this thesis

- International publication of range << B >>, entitled: "Personality-Driven Innovation Adoption: Modeling ChatGPT Diffusion with BERT and Random Forest" published in the journal: "*Ingénierie des Systèmes d'Information*". https://doi.org/10.18280/isi.300515.

- International communication titled "Personality Trait-Driven ChatGPT Adoption," presented at *The Sixth International Symposium on Informatics and Its Applications (ISIA)*, held on December 10–11, 2024, in M'sila, Algeria. https://www.univ-msila.dz/ISIA24/.

- International Conference on *Managing Business through Web Analytics (ICMBWA 2021)*, held at the University of Khemis Miliana, Algeria, on October 13, 2021. The presented paper was titled "COVID-19-Related Information Classification: A Case Study Based on Algerian Online Discussion". Springer, Cham. https://doi.org/10.1007/978-3-031-06971-0_14.