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Teachers' opinion on AI for education: a UTAUT evaluation

Master Thesis

at the Chair for Information Systems and Information Management
(Westfälische Wilhelms-Universität, Münster)

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Date of Submission: 2024-06-07

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1 Abstract

The study proposes a new model for assessing technology adoption in the field of AIED (Artificial Intelligence in Education). This model integrates to UTAUT the construct of Pedagogical Discontentment (PD) as developed in the TCSR (Teacher-Centered School Reform) model in educational psychology. Moreover, it adds to it the school-related contextual moderators of TCSR. Findings suggest that the integration of PD in another model is not immediate, and it can show significance issues. More research on this topic is recommended, since the theoretical base for such integration is still evident.

2 Introduction

The advent of the “AI revolution” (Makridakis, 2017) has seem to come with the release of AI-based tools – especially Large Language Models, LLM – in the last years. The implications are numerous, from the industrial development (Guenduez & Mettler, 2022) to the governmental use (European Commission, 2018). The latter, in particular, appears to be often overlooked if not totally left aside (Medaglia et al., 2021), requiring a deeper analysis.

In fact, taking a closer look, we notice that among government papers not all topics are evenly discussed: healthcare and transportation (European Commission, 2020) indeed receive more attention than, for instance, education. In the past few years, the field of Artificial Intelligence in Education (AIED) has produced various steps ahead, identifying applications (Zawacki-Richter et al., 2019), challenges (Kasneci et al., 2023), opportunities (Chen et al., 2020a), and developing frameworks (Hwang et al., 2020).

Yet not all the paths have been taken: the field of technology adoption, that is, the attempt of finding the elements that influence individuals’ intention to use and actual use of a given technology (for instance, see Venkatesh et al., 2003), has been extensively used also in education (Dwivedi et al., 2011). However, education possesses other useful subfields, such as educational psychology, and its models about changing behavior (for instance, see Woodbury & Gess-Newsome, 2002).

These models focus on the factors that influence teachers’ changes in pedagogical practices (Woodbury & Gess-Newsome, 2002). Thus, since adoption is, conceptually, a type of behavioral change, this study will try to combine the most-used models of technology adoption (Unified Theory on Acceptance and Use of Technology, UTAUT) and conceptual change (Teacher Centered Systemic Reform, TCSR) to predict teachers’ intention to adopt AI tools for education.

To do so, a research question is formulated:

> (RQ1) What are the factors that, as drivers and barriers, influence the use of AIED technologies by teachers?

This research will answer the question above by presenting both research fields’ models and the main findings on AIED and AI-PS (Artificial Intelligence in the Public Sector, since education is part of it) in a literature review (chapter 2). A new model that combines both models’ constructs will be formulated and proposed, based on hypotheses on such constructs’ predictions on adoption (chapter 3). Then, a quantitative analysis will be designed and performed (chapter 4). The results obtained will be presented (chapter 5) and discussed (chapter 6).

3 Literature Review

The following section will conduct a literature review for each of the research fields intercepted in this study: technology adoption; conceptual change models and their application to the school systems; Artificial Intelligence in the Public Sector (AI-PS); Artificial Intelligence in Education (AIED). Finally, there will a subsection explaining the relevant features of the Italian school system.

3.1 Technology Adoption

The acceptance and use of (information) technologies has been an important issue for a few decades now (Dwivedi et al., 2019; Venkatesh et al., 2003). Several models have been proposed, validated, and corrected. In this section, this study will show and explain the theories that concurred in the formation of the most used model (UTAUT) and the changes operated on it that would be useful for the purpose of this study.

3.1.1 Theory of Reasoned Action

Perhaps, the oldest model to have still an influence in today's research is the Theory of Reasoned Action (TRA), firstly presented by Fishbein & Ajzen (1975), in which attitude (A) and subjective norm (SN) directly influence intention (I) to perform a behavior concerning an object (or system, or technology), that, subsequently, influences the actual behavior (B). The concept of SN refers to the "belief that important others think he should or should not perform a given behavior" (Fishbein & Ajzen, 1975, p. 401). The concept of A, instead, "represents a person's general feeling of favorableness or unfavorableness toward some stimulus object" (Fishbein & Ajzen, 1975, p. 216). Regarding the dependent variable, I is "a person's subjective probability that he will perform some behavior" (Fishbein & Ajzen, 1975, p. 288), that eventually influences B.

Explained in an equation,

$$(1)\ B \approx I_{act} = w_1 A_{act} + w_2 SN_{act},$$

Where:

- B = actual behavior
- I_{act} = behavioral intention regarding B
- A_{act} = attitude toward B
- SN_{act} = subjective norm regarding B

- w_1, w_2 = importance weights

However, also the independent variables, A and SN, must be explained. Hence, there are two other equations with A and SN as dependent variables:

(2) $A_{act} = \sum_{i = 1, n} b_i e_i$,

Where:

- b_i = belief that performing B will result in consequence i
- e_i = evaluation of consequence i
- n = number of salient beliefs

And,

(3) $SN_{act} = \sum_{j = 1, m} nb_j mc_j$,

Where:

- nb_j = normative belief that referent j wants subject to perform B
- mc_j = motivation to comply with referent j
- m = number of salient referents

According to Davis (1986), one of the most important novelties of TRA is shifting the focus from the object to the behavior: in fact, besides what the previously given definition of A may look like, in TRA A is A_{act} (as "action") and not A_o (as "object"), as it was conceptualized in some previous models (Fishbein, 1963; Rosenberg, 1956). This novelty created a model that would predict more precisely the correlation between individuals' beliefs – since A is composed by the sum of the beliefs about what the consequences of using an object would be, and the sum of the evaluations of such consequences – and actual behavior.

Another relevant aspect derived by the application of TRA is that it "allows the integration of numerous theoretical perspectives from psychology into MIS [= Management of Information Systems, i.e., the academic sphere to which technology adoption belongs] acceptance research" (Davis, 1986). Hence, it permits the exploitation of a more developed research field, both of its already-validated findings and of its future discoveries – this element contributed significantly into making TRA an influent precursor of the models that followed.

TRA advantages, however, lies also on some of its statements that would further be proven to be incorrect, imprecise, or not fully developed at that time – so that some following models could improve TRA's prediction power. For instance, TRA suggests that all external variables, that is, all constructs that aren't A or SN, influence I ≈ B only indirectly, and that A is formed only by the beliefs and evaluations about the consequences of performing that behavior. However, focusing only on the consequences might be a limited perspective, since the interaction between the individual and the object does involve other processes: in fact, this is the thought that led to the formation of the Technology Acceptance Model (TAM), as firstly proposed by Davis (1986).

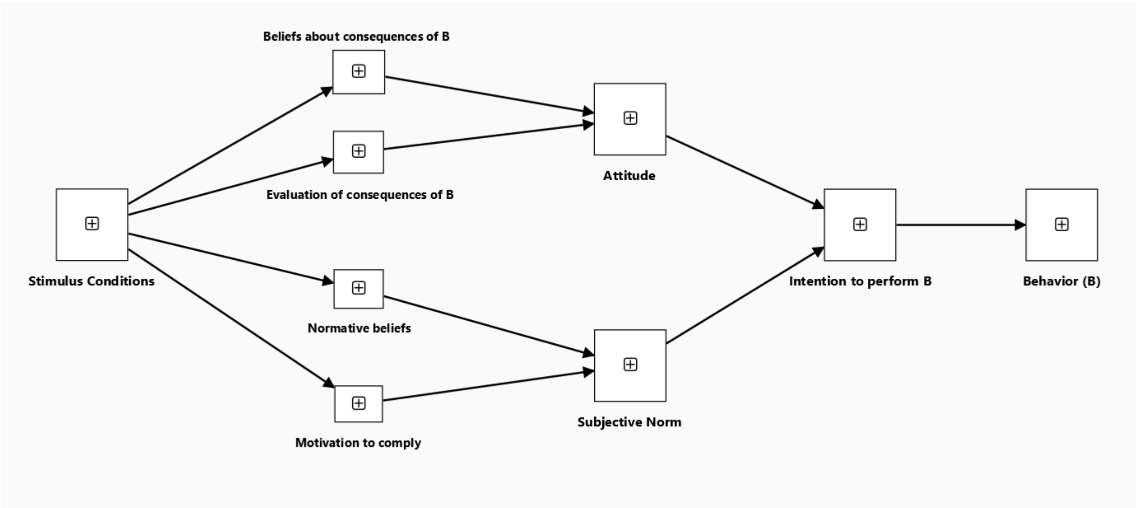

Figure 1: TRA (drawn from Fishbein & Ajzen, 1975)

3.1.2 Technology Acceptance Model

The idea behind it was that the design features of the object/system/technology would influence the cognitive response (Perceived Usefulness, PU, and Perceived Ease of Use, PEOU), that would subsequently impact the affective response (Attitude, A), that would in the end affect behavior (B). TAM can be expressed as the combination of five equations:

(1) $PEOU = \sum_{i = 1, n} \beta_1 X_1 + \varepsilon$

(2) $PU = \sum_{i = 1, n} \beta_1 X_1 + \beta_{n+1} PEOU + \varepsilon$

(3) $ATT = \beta_1 PEOU + \beta_2 PU + \varepsilon$

(4) $BI = \beta_1 ATT + \beta_2 PU + \varepsilon$

(5) $UB = \beta_1 ATT + \varepsilon$

Where:

- X_1 = design feature i, i = 1, n
- PEOU = perceived ease of use
- PU = perceived usefulness
- ATT = attitude toward using (= A_{act} in TRA)
- BI = behavioral intention (= I in TRA)
- UB = actual use of the system (= B in TRA)
- β_i = standardized partial regression coefficient
- ε = random error term

PU is "the degree to which an individual believes that using a particular system would enhance his or her job performance", while PEOU is "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1986, p.26). The distinction between these two constructs improves the model since it integrates some requirements (PEOU, not applied in TRA) to the consequences (PU, applied in TRA) of B.

It can be observed that in TAM the SN from TRA has been eliminated. This happened firstly because there was very little research on the formation of the normative beliefs (Davis, 1986), and secondly because SN was later found to be "particularly weak from a psychometric standpoint" (Davis et al., 1989, p. 998) when empirically tested, which resulted in lack of significant SN-I relationship.

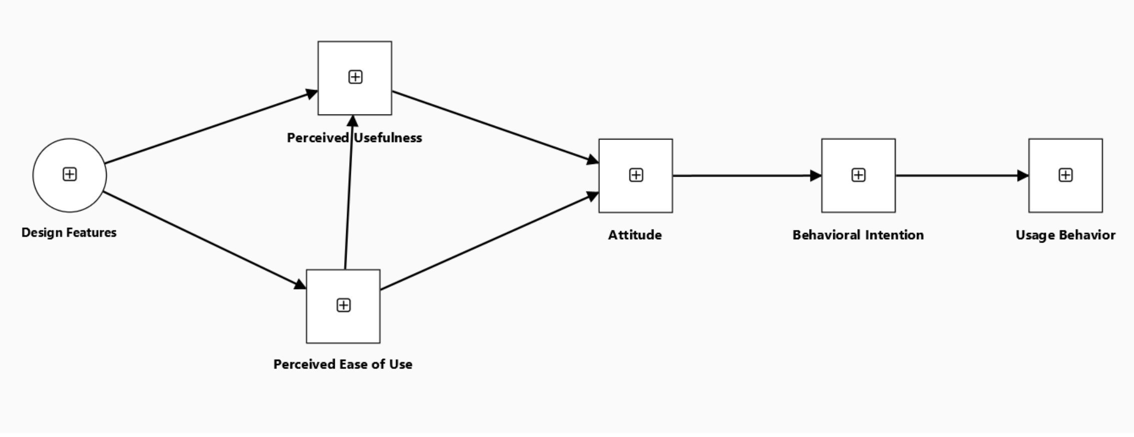

Figure 2: TAM (drawn from Davis, 1986)

3.1.3 Theory of Planned Behavior

One of the limitations of TRA is related to the perception of the subject of not being in control over the performance of B (Davis, 1986; Fishbein & Ajzen, 1975). This lack of *volitional* control is supposed to be present when an individual believes that "lacks the ability or resources to carry out an intended behavior" (Davis, 1986, p. 21). TAM did not solve this issue, that was instead carried out by the Theory of Planned Behavior (TPB). In this model (Ajzen, 1991), ATT, SN, and Perceived Behavioral Control (PBC) influence BI, that subsequently with PBC does influence UB.

As noted by (Ajzen, 1991) itself, TPB differs from TRA because of PBC – the other constructs and their related relationships remain unchanged. PBC is not derived from Rotter's (1966) concept of perceived locus of control, since it concerns the degree of difficulty or ease in performing a behavior, and it is meant to be stable – if not fixed – in different measurements over time; although more similar to PBC than Rotter's, Atkinson's (1964) theory of achievement motivation also is not at the origin of PBC since it worked on a general disposition that would lead the subject "from one situation to another" (Atkinson, 1964, p. 242). Rather, the closest concept to PBC is perceived self-efficacy, developed by Bandura (1977; 1982) as a belief on the "how well" (Bandura, 1982, p. 122) an individual can perform a behavior.

The equation used to express PBC is:

(1) $PBC = \sum_{i = 1, n} c_i p_i$

Where:

- c_i = control beliefs
- p_i = perceived power of each control belief
- n = number of salient control beliefs

The formation of the control beliefs presents a double origin: some first-hand information derived from past behavior; some processed information, obtained from the experiences of acquaintances (Ajzen, 1991). The second procedure is, indeed, the most frequent. Thus, concluding, PBC introduces the beliefs over resources and opportunities as even important as normative beliefs and beliefs about consequences in the formation of the internal independent variables.

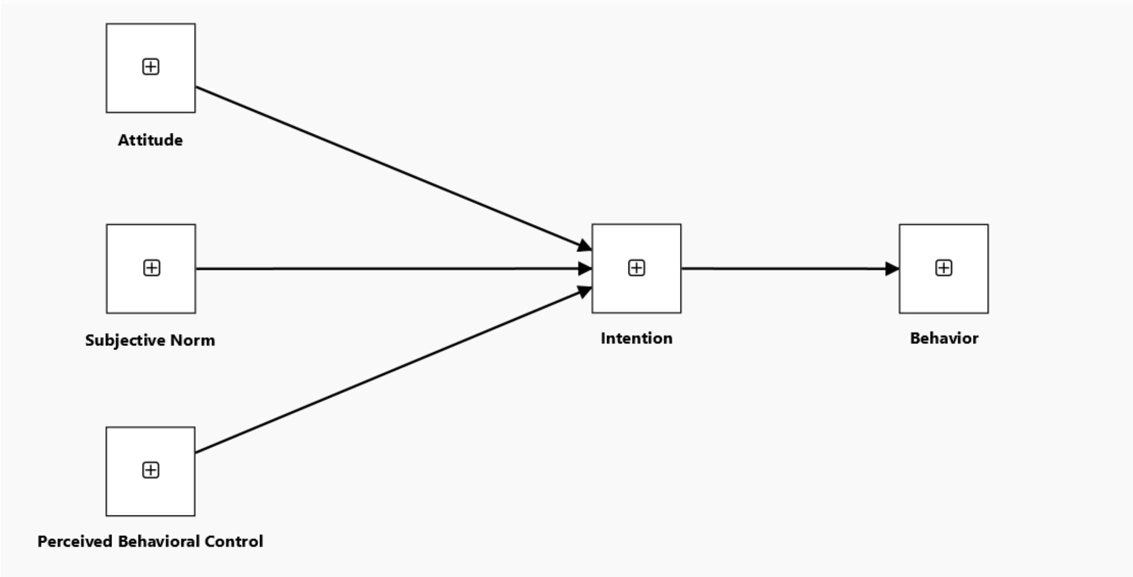

Figure 3: TPB (drawn from Ajzen, 1991)

3.1.4 Other variations of TRA, TAM, TPB

The three models explained so far have had numerous variations and followers. The ones that are relevant for this research are:

- TAM2 is an extension of TAM in which, besides PU and PEOU influencing ATT, it was finally added SN from TRA. All the constructs used refer to the definitions of the original models (Ajzen, 1991; Davis, 1986; Fishbein & Ajzen, 1975). The model is proposed by Venkatesh et al. (2000) and has been substantially applied in Information Systems research.

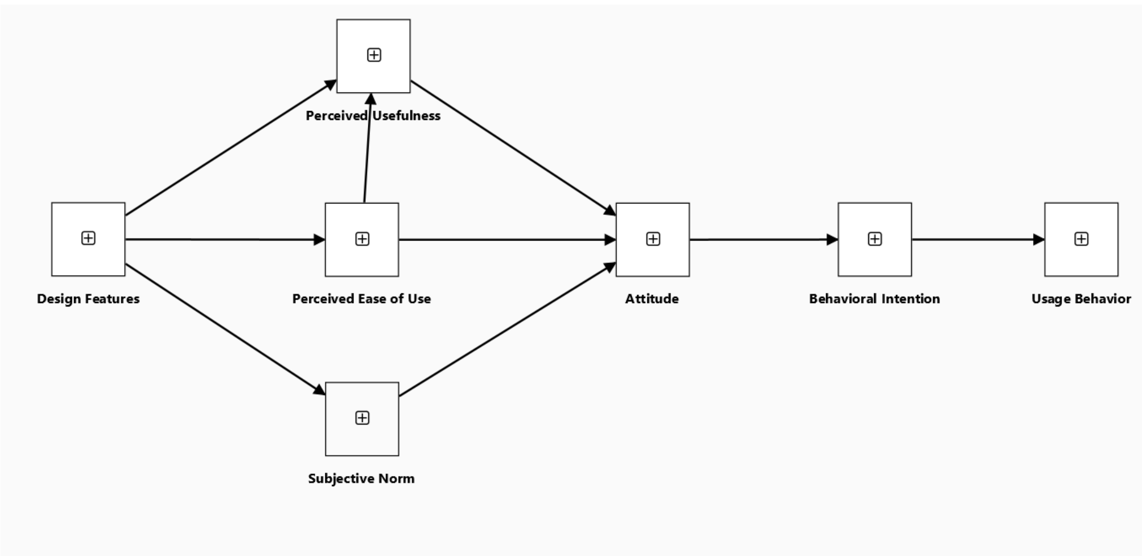

Figure 4: TAM2 (drawn from Venkatesh et al. 2000)

- The Decomposed Theory of Planned Behavior (DTPB) uses all the constructs from TRA/TPB – namely, ATT, SN, and PBC. However, it “decomposes” them in some of the previously explained beliefs and in others explained in the following subsections. The model is proposed by Taylor & Todd, (1995b).

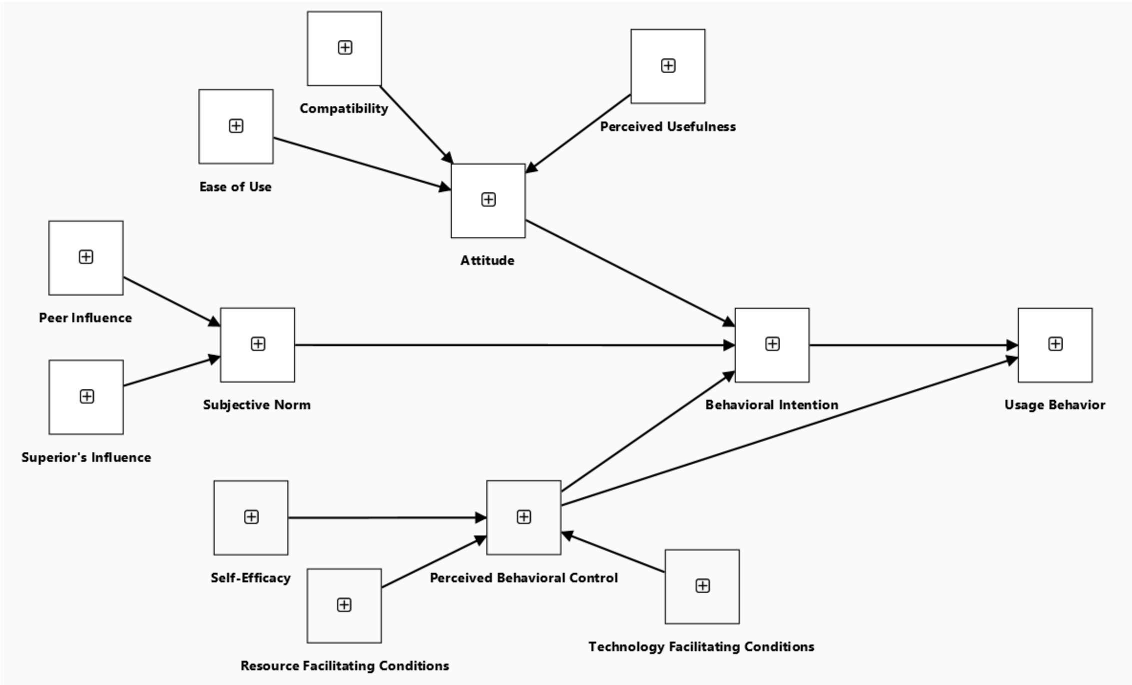

Figure 5: DTPB (drawn from Taylor & Todd, 1995b)

- The Combined TAM and TPB (C-TAM-TPB) uses all the constructs from TRA/TPB – namely, ATT, SN, and PBC – and adds to them PU from TAM. All the constructs used refer to the definitions of the original models (Ajzen, 1991; Davis, 1986; Fishbein & Ajzen, 1975). The model is proposed by Taylor & Todd, 1995a).

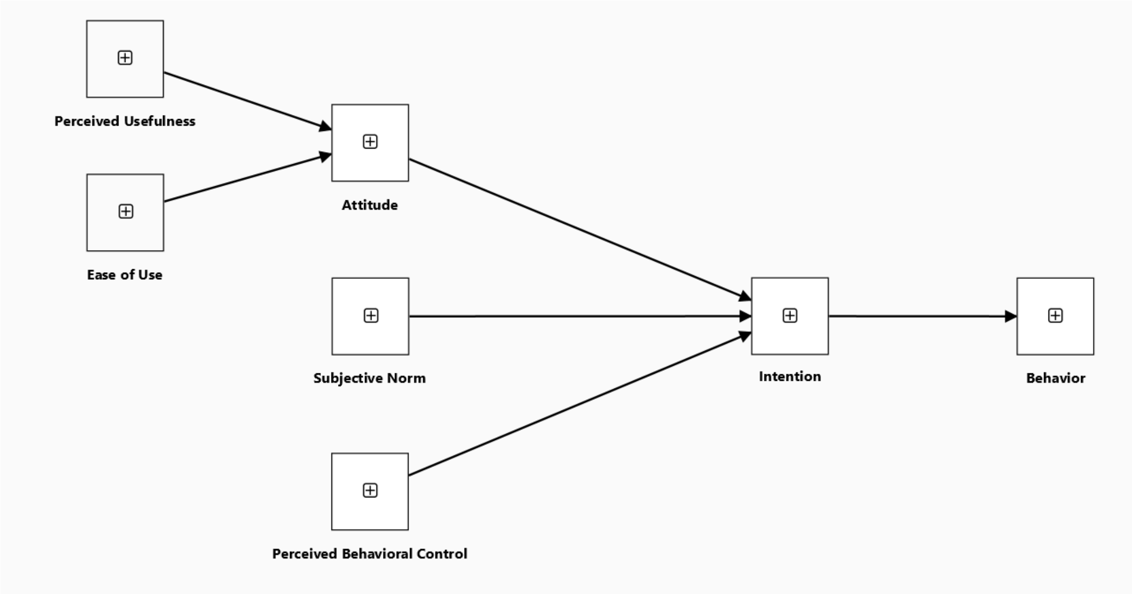

Figure 6: C-TAM-TPB (drawn from Taylor & Todd, 1995a)

These theories have the merit of fostering the use of TRA/TAM/TPB constructs. However, there are four other models that, with different concepts and rationales, have contributed to developing the (information) technology adoption research field.

3.1.5 Motivational Model

As the name suggests, the Motivational Model (MM) proposes to understand why humans perform a specific activity. Well-validated research suggests that there are two classes of motivated behavior: the first one, called *intrinsic motivation* refers to the possible "pleasure and satisfaction inherent in the activity" (Vallerand, 1997, p. 271); the second one, *extrinsic motivation*, refers to behavior performed "to achieve some separable goal, such as receiving rewards and avoiding punishments" (Vallerand, 1997, p. 271).

Thus, MM has been built on the relationship between these two types of motivations. Vallerand (1997, p. 271-272) identifies three major categories in which such analyses can be identified: the first one concerns the "immediate effects" of situational variables "on intrinsic motivation" (an example is Deci, 1971); the second one focuses on both "determinants and outcomes" of both types of motivation applied to "specific life contexts" (an example is Deci et al., 1981); the final category assesses "the relationship between intrinsic and extrinsic motivation as a global motivational orientation" (an example is Deci & Ryan, 1985).

To provide a more comprehensive view, Vallerand (1995) has formulated a Hierarchical Model of Intrinsic and Extrinsic Motivation, that is, a framework to analyze all these relationships. The framework is set to explain how such motivations – and *amotivation*, otherwise called lack of motivation (see Deci & Ryan, 1985) – are influenced by social factors at global, contextual, and individual level; are mediated by the mediators, that are autonomy, competence, and relatedness; explain the affective, cognitive, and behavioral consequences.

Hence, in short, MM is the name used to refer to all frameworks and hypothesized models concerning the study of the influence of motivation on behavior. For what concerns technology adoption, the first application of MM is found in Davis et al., (1992). Although it hasn't resulted in a prolific literature body, the distinction between extrinsic, intrinsic and amotivation is still of interest in the technology adoption research field.

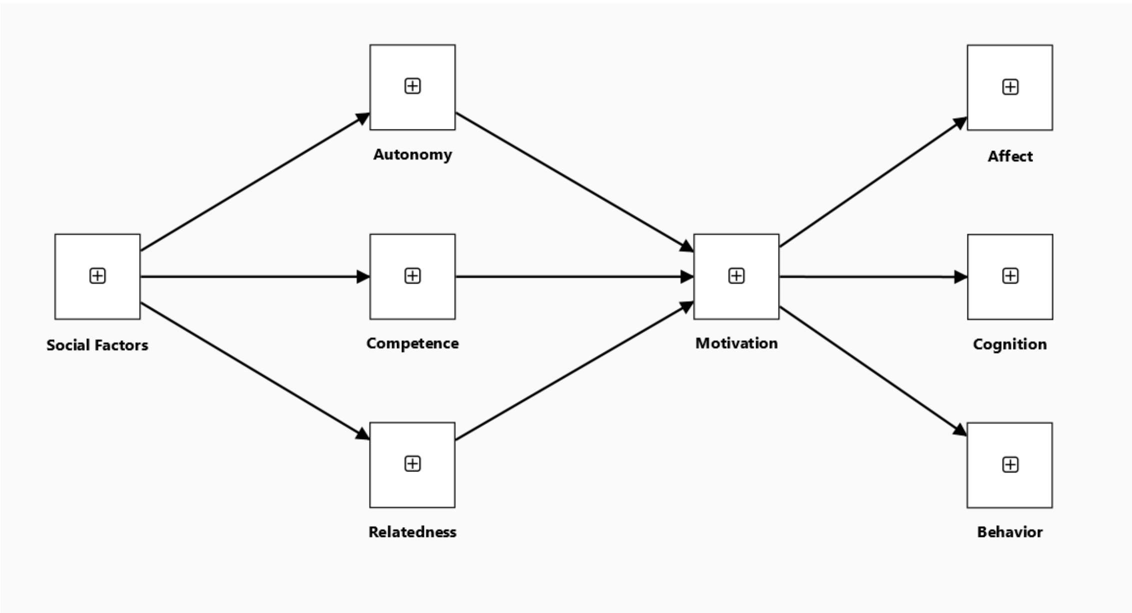

Figure 7: Hierarchical MM (drawn from Vallerand, 1995)

3.1.6 Model of PC Utilization

The Model of PC Utilization (MPCU) was developed by Thompson et al. (1991) to predict PC utilization – that hence is the dependent variable. Triandis (1980) argued that "behavior is determined by what people would like to do (attitudes), what they think they should do (social norms), what they have usually done (habits), and by the expected consequences of their behavior" (Thompson et al., 1991). He organized the model on the following steps: habit hierarchies influence affect toward use; social factors, affect toward use, and perceived consequences influence behavioral intention; behavioral intention and facilitating conditions influence actual behavior; actual behavior influences habit hierarchies. The constructs are defined as follows:

- Social factors: “the individual's internalization of the reference groups' subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations” (Triandis, 1980, p. 210).
- Affect: “the feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act” (Triandis, 1980, p. 211).
- Perceived consequences: the expected consequences of the behavior (Triandis, 1980).
- Facilitating conditions: “objective factors, 'out there' in the environment, that several judges or observers can agree make an act easy to do” (Triandis, 1980, p. 205).
- Habit: “situation-behavior sequences that occur without self-instruction. The individual is usually not conscious of these sequences” (Thompson et al., 1991, p. 130).

The modified version proposed by Thompson et al. (1991) removes the multiple steps used by Triandis (1980) – in particular it removes the existence of behavioral intention and habit hierarchies – and presents all the factors that directly influence behavior, or PC utilization: long-term consequences of PC use; job fit with PC use; complexity of PC use; affect toward PC use; social factors influencing PC use; facilitating conditions for PC use. Being most of these constructs the same as the ones used by Triandis (1980), the added ones are defined as follows:

- Complexity (of PC use): “the degree to which an innovation is perceived as relatively difficult to understand and use" (Thompson et al., 1991, p. 128).
- Job fit (with PC use): “the extent to which an individual believes that using a PC can enhance the performance of his or her job” (Thompson et al., 1991, p. 129).

The novelties of the two versions of the model are numerous and their importance must be outlined here. Concerning Triandis (1980):

- Social factors are expressed as direct predictors of behavioral intention for the first time – before they had been included as “external variables” in TRA and they kept being evaluated as such in both TAM and TPB.
- Decomposing “attitude” is a necessary step for the development of a more precise model: as reported by Thompson et al. (1991), it has been pointed out that attitude

is “an imprecise term that is more useful for discussions where precision is not necessary” (Thompson et al., 1991, p. 127), considering that “attitudes involve cognitive, affective, and behavioral components[, and, for instance,] the cognitive component of attitudes involves beliefs” (Thompson et al., 1991, p. 126) – which means that perceived consequences, and affect can be included in a general category of attitude, but for the sake of precision, they are distinguished in this model due to their belonging to different components of it.

- The introduction of Facilitating Conditions (FC from now on) will have a huge impact on technology adoption research, since it is the first introduction of objective elements that are not related to the personal sphere.

- The introduction of Habit, although not relevant for this specific study, will also have a huge impact on technology adoption research: this construct put out the basis for giving an alternative to the volitional control of TPB – not for the control component, but for the “active will” that the *volitional* component requires. Moreover, it represents the incompleteness of the MM – since it stated that only the active types of motivations, or non-motivations, can influence a behavior.

The version proposed by Thompson et al. (1991), instead, influenced technology adoption research with the following acts:

- The translation of the Triandis’s (1980) model into IS research. It is the first example of the translation of a model from a different field into IS from TRA. Thus, it is the first application of the possibility introduced by TRA – and mentioned previously – of translating psychology-related concepts and constructs into IS research.

- The decomposition of “Perceived Consequences” from Triandis’s (1980) model into long-term consequences of PC use, job fit with PC use, and complexity of PC use. This newly conceptualized constructs permit the integration of this model with TAM, since job fit and complexity present strong similarities with PU and PEOU respectively. Considering the previously analyzed relationship between TRA, TAM, and TPB, this action permitted an integration not only with TAM, but also with the other two models.

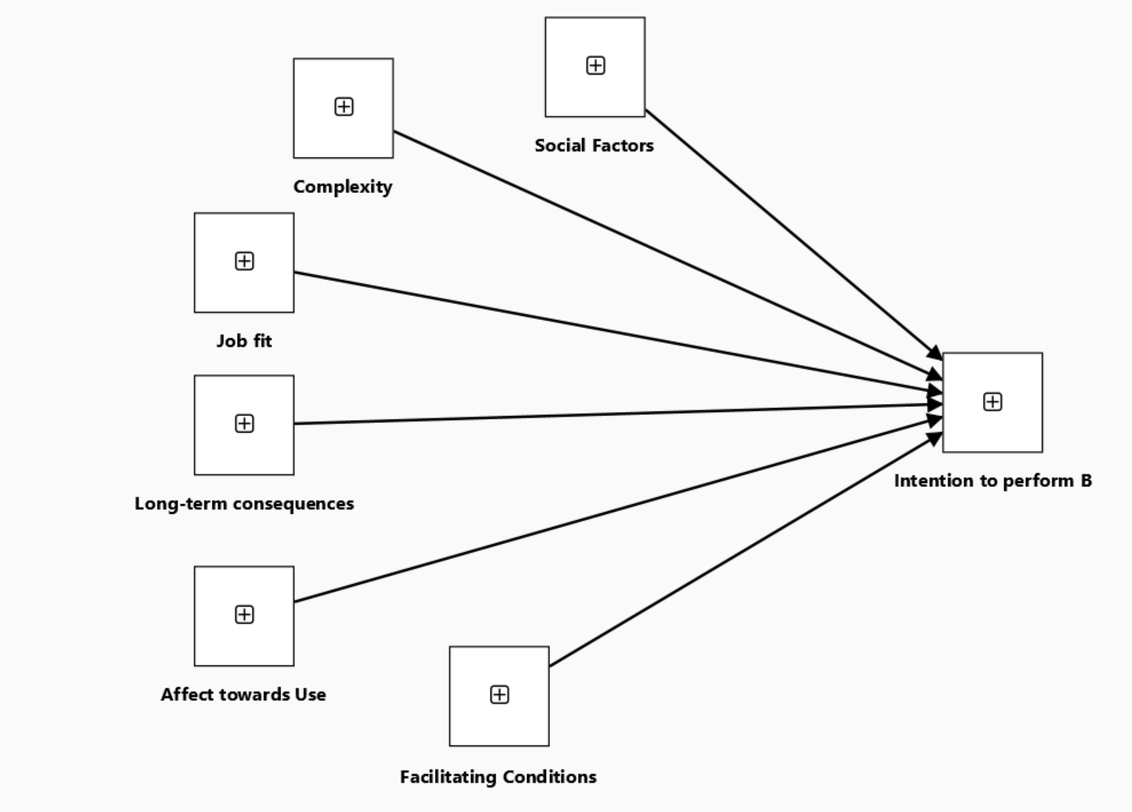

Figure 8: MPCU (drawn from Thompson et al., 1991)

3.1.7 Innovation Diffusion Theory

Innovation Diffusion Theory (IDT) has been proposed by Moore & Benbasat (1991) using the five characteristics of an innovation which affect its “rate of diffusion” (Moore & Benbasat, 1991, p. 193). IDT focuses on explaining technology use by analyzing individuals’ perceptions on such technology. The original five characteristics are:

- Relative Advantage: the degree to which an innovation is perceived as being better than its precursor.
- Compatibility: the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters.
- Complexity: the degree to which an innovation is perceived as being difficult to use.
- Observability: the degree to which the results of an innovation are observable to others.
- Trialability: the degree to which an innovation may be experimented with before adoption.

Instead, the two characteristics further identified by Moore & Benbasat (1991), and added to the model, are:

- Image: the degree to which use of an innovation is perceived to enhance one's image or status in one's social system.
- Voluntariness of Use: the degree to which use of the innovation is perceived to be voluntary, or of free will.

These seven constructs were empirically tested four times. After these processes took place, Moore & Benbasat (1991) removed, changed, merged, or modified some characteristics. The final list comprehends:

- Relative Advantage, as previously defined.
- Ease of use, derived from TAM, that substitutes Complexity, maintaining the same meaning.
- Image, as previously defined.
- Visibility, i.e., "the degree to which one can see others using the system in the organization" (Venkatesh et al., 2003, p. 431).
- Compatibility, as previously defined.
- Results Demonstrability, i.e., "the tangibility of the results of using the innovation, including their observability and communicability" (Moore & Benbasat, 1991, p. 203). Thus, it substitutes, but also comprehends as part of a greater concept, the previously explained construct of Observability.
- Voluntariness of Use, as previously defined.

The importance of IDT in technology adoption resides in two main elements, that are, an improved specification of constructs already-used in other models – for instance, although Relative Advantage approximately corresponds to PU from TAM, Compatibility and Results Demonstrability can also be considered as part of the constructs that gather around the beliefs and evaluations on the consequences of the behavior, although on topics that in the previous models weren't considered.

The second element on importance of IDT is the introduction of the concept of Voluntariness of Use. Moore & Benbasat (1991) explicitly precised that whether an individual is forced to use a technology or not can significantly change the approach that individual will have toward that behavior. Moreover, they argued that in many studies such dimension is represented factually, i.e., researchers may declare whether a technology is objectively imposed to the workers or not. However, an employee might *feel* an imposition even when such system is not mandatory, but rather just proposed by the management. This aspect, hence, continues the path started with Fishbein & Ajzen (1975), according to which the focus in on the beliefs on the behavior performed with the object – and not the beliefs on the object per se.

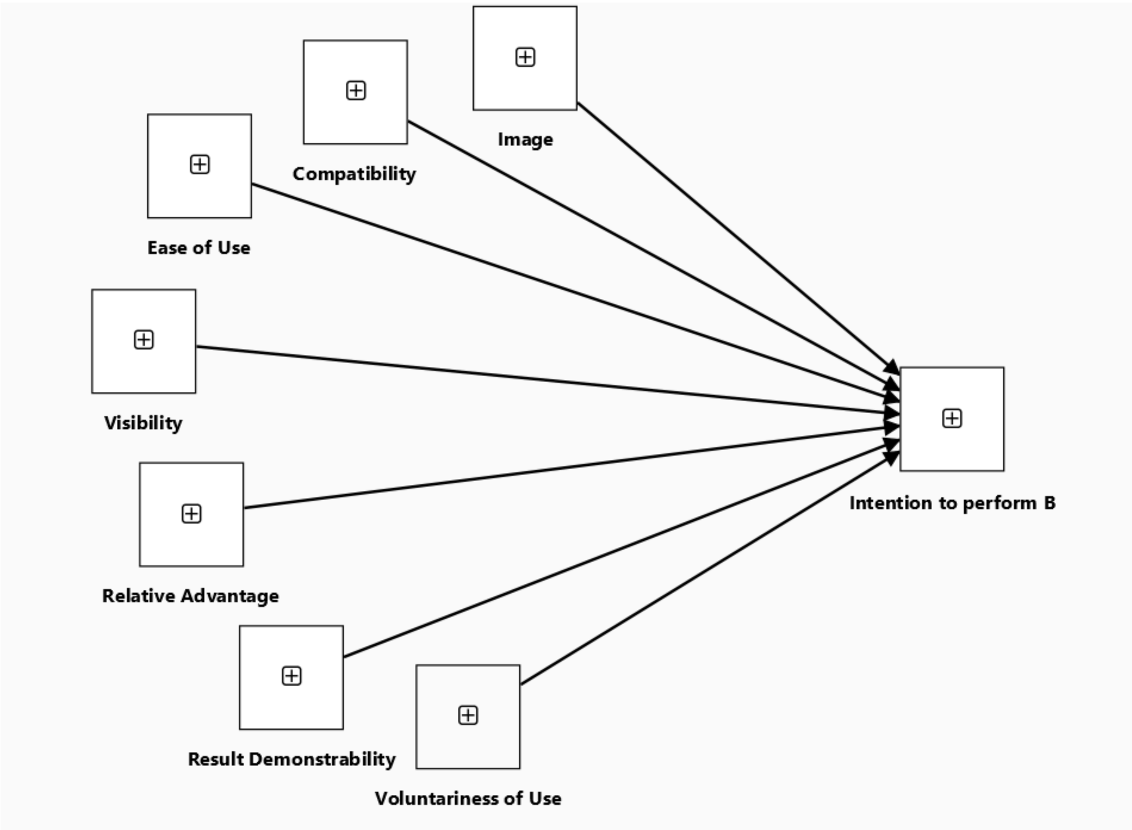

Figure 9: IDT (drawn from Moore & Benbasat, 1991)

3.1.8 Social Cognitive Theory

The Social Cognitive Theory (SCT) has been developed by Bandura (1977, 1982) and it asserts that two elements can modify a performance (PF): cognitive influence and behavior modelling. In SCT, cognitive influence is composed by two concepts: outcome expectations (OE, subsequently divided in OE-Performance and OE-Personal) and self-efficacy (SE; when applied to technology adoption is computer self-efficacy, or CSE). Instead, behavior modelling (BM) refers to individuals inspired and influenced by "observing others performing [that…] behavior" (Compeau & Higgins, 1995a, p. 120).

OE has been extensively used for technology adoption research already before Compeau & Higgins' (1995a) paper: concerning the present study, this concept reminds of beliefs about consequences in TRA and TPB, PU in TAM, and perceived consequences in MPCU. SE, instead, appeared only in TPB as PBC, while BM was mentioned only in IDT as Visibility.

The application of SCT to technology adoption demonstrated some limitations: Compeau & Higgins (1995a) formulated nine hypotheses, six coming from the original model (BM influencing CSE, OE, PF; CSE influencing OE and PF; OE influencing PF) and three added to it (prior performance, or PPF, influencing CSE, OE, PF), and tested them four times. The results did not fully show the outcomes expected: CSE was the most significant predictor since it did influence both OE and PF; BM mostly, but not always, influenced CSE, OE, and PF; OE does influence PF but in the opposite direction than the one predicted – thus, a positive expected outcome mostly incurred in a negative performance; finally, PPF positively influence PF, negatively influence OE, and partially positively influence SE.

The good results obtained by self-efficacy and the lack of its use brought Compeau & Higgins to write another paper (1995b) to confirm the possible implementation of self-efficacy into the information systems adoption research, proposing and validating a measurement scale. The definition of self-efficacy used for that study is derived from Bandura (1982). It concerns "[p]eople's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has but with judgments of what one can do with whatever skills one possesses" (Bandura, 1982, p. 391). Once again, self-efficacy proved its significance in predicting computer adoption.

In this second study, due to the unexpected results of the first one, the proposed model was enlarged to contain many more constructs: it implied a first part in which social elements, such as Encouragement by Others (similar to SN of TRA), Others' Use (equal to BM), and Support (roughly corresponding to FC of MPCU) do influence both CSE and OE. Secondly, it stated that CSE influence OE, Affect (same as Affect from MPCU), Anxiety (derived from Igbaria, et al., 1989; Webster, et al., 1990), and Usage (i.e., actual behavior). Thirdly, OE influence Affect and Usage. Finally, Affect and Anxiety influence Usage. All the paths have been found significant.

After the empirical evaluations, the social elements are not considered part of the emerging core constructs of IDT in IS research, that then are:

- Outcome Expectations – Performance: "the performance-related consequences of the behavior. Specifically, performance expectations deal with job-related outcomes" (Compeau & Higgins, 1995b, in Venkatesh et al., 2003, p. 432).

- Outcome Expectations – Personal: “the personal consequences of the behavior. Specifically, personal expectations deal with the individual esteem and sense of accomplishment (Compeau & Higgins, 1995b, in Venkatesh et al., 2003, p. 432).
- Self-Efficacy: “judgment of one’s ability to use a technology (e.g., computer) to accomplish a particular job or task” (Venkatesh et al., 2003, p. 432). This definition was proposed to simplify and apply to the IS context the previously mentioned definition by Bandura (1986).
- Affect: “an individual’s liking for a particular behavior (e.g., computer use)” (Venkatesh et al., 2003, p. 432).
- Anxiety: “evoking anxious or emotional reactions when it comes to performing a behavior (e.g., using a computer)” (Venkatesh et al., 2003, p. 432).

The importance of this model relies on stating for the first time that self-efficacy and prior experience with a technology are important predictors of information systems adoption. Moreover, it is the first model that shows the importance of the integrations of various elements of the different models covered so far, demonstrating that to a more complex way of adoption model creation is required.

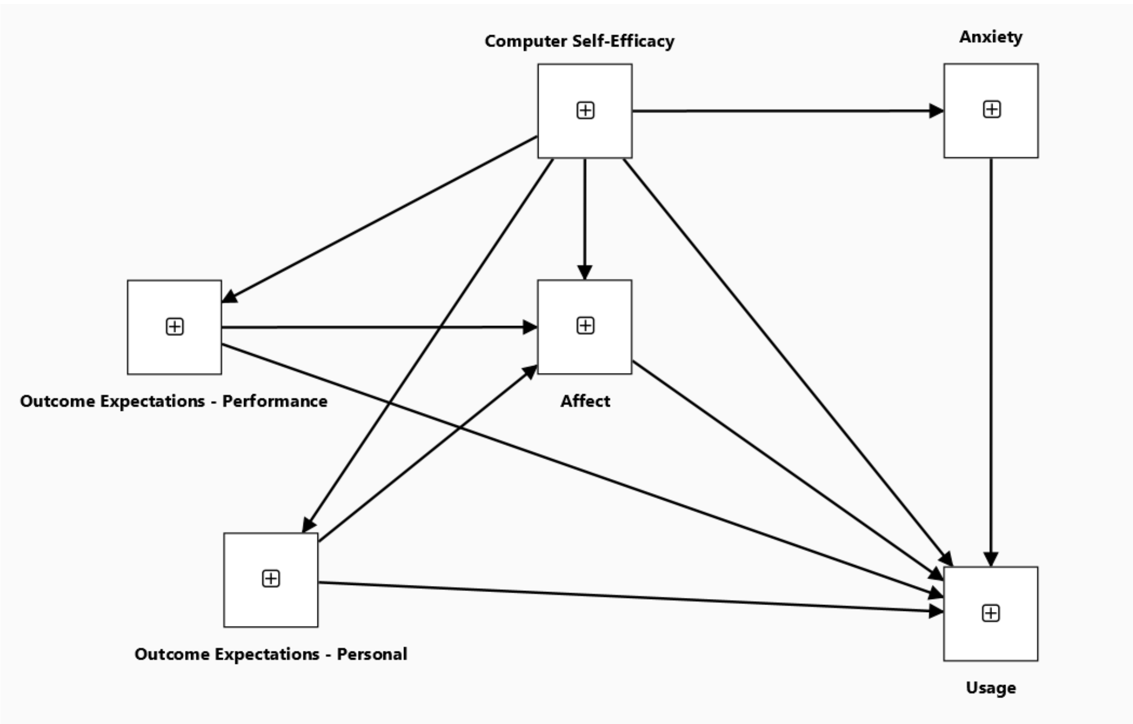

Figure 10: SCT (drawn from Compeau & Higgins, 1995b)

3.1.9 Unified Theory of Acceptance and Use of Technology

The plurality of the models proposed so far caused the "need for a review and synthesis in order to progress toward a unified view of user acceptance" (Venkatesh et al., 2003, p. 426). Thus, Venkatesh et al. (2003) reviewed the existing literature and empirically compared the theories. As a result, it proposed a Unified Theory of Acceptance and Use of Technology (UTAUT) that merged most of the constructs analyzed so far into a single view. The constructs used as direct influencer of Behavioral Intention (BI) or Use Behavior (UB) are:

- Performance Expectancy (PE) is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). It is derived from Perceived Usefulness from TAM, Extrinsic Motivation from MM, Job-fit from MPCU, Relative Advantage from IDT, Outcome Expectations from SCT. PE directly influences BI.

- Effort Expectancy (EE) is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). It is derived from Perceived Ease of Use from TAM, Complexity from MPCU, Ease of Use from IDT. EE directly influences BI.

- Social Influence (SI) is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). It is derived from Subjective Norm from TRA, TAM, TPB, DTPB, C-TAM-TPB, Social Factors from MPCU, Image from IDT. SI directly influences BI.

- Facilitating Conditions (FC) is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). It is derived from Perceived Behavioral Control from TPB, DTPB, C-TAM-TPB, Facilitating Conditions from MPCU, Compatibility from IDT. FC directly influence UB.

Additionally, Venkatesh et al. (2003) inserts some moderators into the model. Although some of the previously presented models used some moderators, they weren't analyzed since such papers did not present them as at the center of their analysis. Thus, they are introduced here:

- Gender: the idea that gender could influence behavioral intention or actual behavior was present, in the previous models, only in TAM2. In the UTAUT model it is supposed to moderate PE to BI, EE to BI, SI to BI.

- Age: the idea that age could influence behavioral intention or actual behavior was present, in the previous models, only in TPB. In the UTAUT model it is supposed to moderate PE to BI, EE to BI, SI to BI, FC to UB.

- Experience: the idea that experience could influence behavioral intention or actual behavior was explicitly included, in the previous models, in C-TAM-TPB, MPCU, IDT, and implicitly included in TRA, TAM, TPB. In the UTAUT model it is supposed to moderate, EE to BI, SI to BI, FC to UB.

- Voluntariness of Use: the idea that voluntariness of use could influence behavioral intention or actual behavior was never present in the previous models, although its possible impact was discussed but never tested in TRA, TAM2, IDT. In the UTAUT model it is supposed to moderate only SI to BI.

The study also stated that some constructs relevant to behavior prediction in previous models would not be treated as such in UTAUT. Hence, UTAUT does not include the following concepts as direct determinants of BI/UB:

- Self-Efficacy (SE) is not specifically defined in Venkatesh et al. (2003). It is derived from Perceived Behavioral Control from TPB, DTPB, C-TAM-TPB, Self-Efficacy from SCT.

- Anxiety (AX) is not specifically defined in Venkatesh et al. (2003). It is derived from Anxiety from SCT.

- Attitude toward Use (AT) is defined as “an individual's overall affective reaction to using a system” (Venkatesh et al., 2003, p. 455). It is derived from Attitude toward Behavior from TRA, TAM, DTPB, C-TAM-TPB, Intrinsic Motivation from MM, Affect toward Use from MPCU, Affect from SCT.

The results of the empirical evaluation of the UTAUT model showed that all hypotheses were correct. Particularly interesting is the effect of moderators: in fact, all the paths to BI or UB – besides BI to UB itself – are moderated by at least one – but in most cases more than one – of the previously listed moderators. In particular for Age and Gender, these findings are impressive since they have been almost ignored by previous research on technology acceptance.

Another important evaluation concerns the confirmation of non-significance in the paths from SE, AX, AT to BI. More specifically, their significance has been rejected by the empirical evaluation because their effect is “being captured by effort expectancy” (Venkatesh et al., 2003, p. 468) – that is, their presence as predictors of BI is redundant with EE.

This redundance, however, does not apply to such constructs in case they are included in the models as predictors, or antecedents, of other constructs besides BI and UB: in fact, Venkatesh et al. (2003) included the possibility for SE or system characteristics to be so, as proposed by previous literature (Davis, 1986; Venkatesh, 2000), or even to other determinants not analyzed in that paper.

As it can be imagined, this was the case: despite its unprecedent influence in the field, the UTAUT model has been amended several times – also by some of the original authors themselves (for instance, see Venkatesh et al., 2012). For what concerns this study, only three groups of innovations within – or outside but similar to – the model will be presented and analyzed. Their impact explains the part of the model proposed for the empirical evaluation of this research that has not been explained so far.

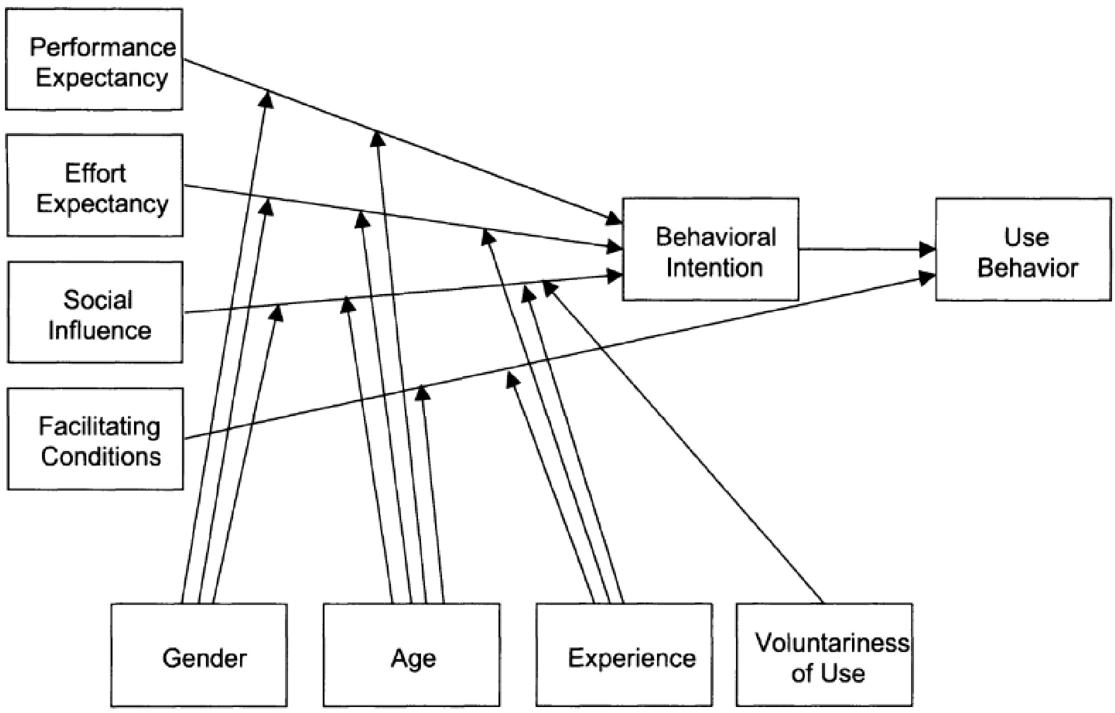

Figure 11: UTAUT (from Venkatesh et al., 2003)

3.1.9.1 Meta-analyses of UTAUT: new constructs

A meta-analysis is a statistical method by which data from single studies is assimilated (Field, 2017). Over the years, many meta-analyses have been done on the UTAUT model (Tamilmani et al., 2020). Some of them did only revise the studies that presented the model as originally developed (for instance, see Taiwo & Downe, 2013). Some others, instead, analyzed also the integrations of new constructs. For instance, Dwivedi et al. (2011) performed such analysis on the studies that applied the model until that moment. The findings suggested, firstly, that most of the papers did not apply the model entirely or cited it just for the sake of it: in fact, of 450 accessible articles, only 43 were found using UTAUT.

Of the 43 usable articles, 22 of them used external variables – i.e., those that were not included in the original model. The most used among them were attitude, anxiety, self-efficacy, perceived risk, and perceived credibility. The path analysis revealed that perceived risk, computer self-efficacy, attitude, trust, and experience have definitely a significant influence on BI. On the contrary, anxiety and perceived credibility did not present a significant impact, and self-efficacy had a mixed influence. Other interesting results were the significant impact of computer self-efficacy on EE, and of IT knowledge on FC.

Venkatesh et al. (2016), instead, reviews the extensions operated by the other papers categorizing them in four novelties: new exogenous mechanisms, new endogenous mechanisms, new moderation mechanisms, and new outcome mechanisms. Here will be considered only some the first two. Among the most used exogenous extensions are perceived innovativeness, computer self-efficacy, organizational characteristics. Among the most used endogenous extensions are trust, self-efficacy, anxiety, attitude, perceived risk.

3.1.9.2 Reconceptualization of UTAUT (AT-UTAUT)

Some studies performed a meta-analysis but didn’t stop their research there. Rana et al. (2017), for example, after testing the UTAUT model and comparing it to other technology acceptance models (TRA, TAM, TPB, and so forth), provided a new conceptualization of the theory that was empirically evaluated.

In detail, the study suggested that:

- Attitude (AT) operated as a mediator between some of the original endogenous constructs and behavioral intention. More specifically, PE, EE, and SI did not influence directly BI, but rather were mediated by AT – thus, AT directly influences BI.

- Anxiety (AX) was introduced as an endogenous construct that would influence BI only through the mediation of AT.
- SI and FC are predictors of PE: for both, Rana et al. (2017) found some UTAUT-related literature supporting such hypothesis; moreover, only for SI also a precedent in Venkatesh et al. (2000), that, developing the TAM2 model, considered Social Norm (SN, a root for SI) a predictor of Perceived Usefulness (PU, a root for PE).
- BI is the only dependent variable of the model, since UB is not evaluated. Thus, FC does not influence UB, as in the original theory, but rather would influence only BI – also, as a component of the FC to PE mechanism, in which the concept of "Training" played a huge part. Such hypothesis is supported by some literature on eGovernment, that was at the center of Rana et al. (2017).

All the hypotheses were found correct: the relationships were all positive and significant, and their constructs were found to be reliable, valid, and homogeneous.

This wasn't the only study to perform such analysis: Dwivedi et al. (2019) did not perform a true meta-analysis, but it moved in the similar direction as Rana et al. (2017): in fact, it independently analyzed all the models that Venkatesh et al. (2003) tested before the formulation of UTAUT – i.e., TRA, TAM, TAM2, TPB, DTPB, C-TAM-TPB, MM, MPCU, IDT, SCT – and added some others, such as IS Success Model, Extended IS Success Model, Task-Technology Fit Model, TAM Extension, TAM3, Model of Acceptance with Peer Support, UTAUT2.

The objective of that study was to include the construct AT as an endogenous variable of UTAUT, since it was vastly present in the technology acceptance literature, but it was absent in UTAUT and UTAUT2. They defined AT as "an individual's positive or negative feelings about performing the target behaviour" (Dwivedi et al., 2019, p. 724). Thus, they proposed that the new core UTAUT model should have been formulated as follows:

- PE, EE directly influence AT.
- PE, EE, SI, FC, AT directly influence BI.
- FC, BI directly influence UB.

This model was then empirically evaluated. All the hypotheses resulted being correct. To them, from the test it emerged that three paths should have been added to such model. They comprehended:

- SI, FC directly influencing AT.
- AT directly influencing UB.

If AT to UB is confirmed also by TAM, the other results must be looked at with some limitations: according to the literature, FC to AT emerged to be existing only in a mandatory setting. SI to AT was confirmed due to two mechanisms, namely, internalization, and identification that influence beliefs and social status change, that would then influence attitudes. However, social status change is not applicable in every context; thus, the path might not be true or might be weak.

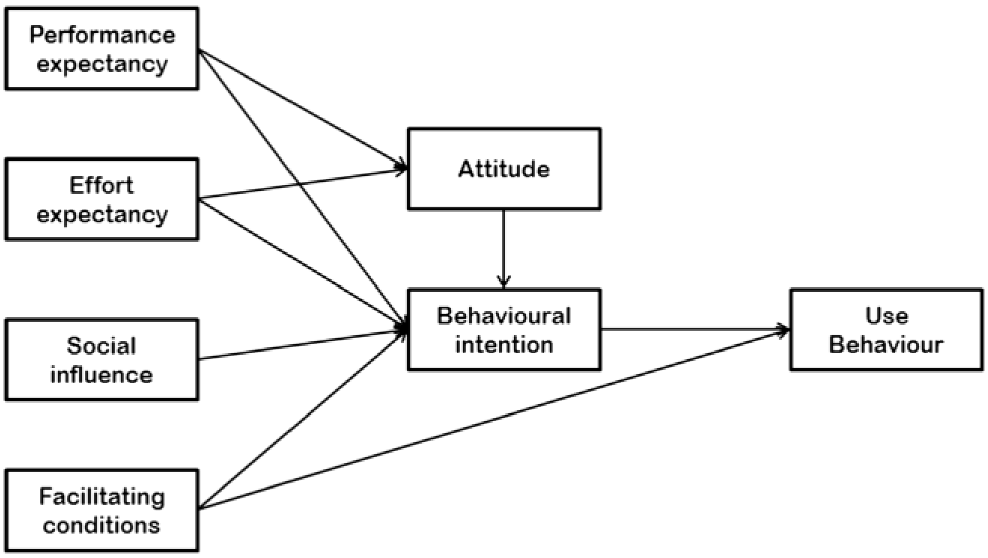

Figure 12: AT-UTAUT (from Dwivedi et al., 2019)

3.1.9.3 Information Systems adoption continuance

As of now this study has showed and explained only models that focus on the relationships between beliefs and actions in a specific moment of time. However, such dynamics do not operate in snapshots, but rather in a continuum: in fact, the lack of longitudinal studies, in favor of cross-sectional ones, has been addressed in numerous moments (see for instance Venkatesh et al., 2003; Venkatesh et al., 2016).

The first research to develop a model that would purposefully investigate changes in beliefs and attitudes – and hence behaviors – in technology acceptance is Bhattacherjee

(2001). To do so, as previously performed by Davis (1986) with psychology and IS literature, it combined two research fields, namely consumer behavior literature and IS usage. Based on on TRA, TPB, and IDT, Bhattacherjee (2001) derived the post-acceptance model of IS continuance that is structured as follows:

- Confirmation influences positively and directly Perceived Usefulness and Satisfaction.
- Perceived Usefulness influences positively and directly Satisfaction and IS Continuance Intention.
- Satisfaction influences positively and directly IS Continuance Intention.

The findings of the empirical evaluation supported all the hypotheses as described above.

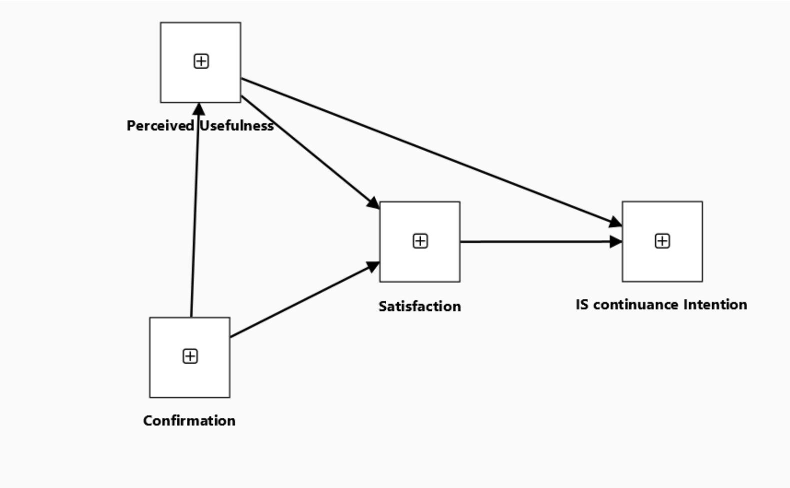

Figure 13: IS CONTINUANCE (drawn from Bhattacherjee, 2001)

However, the author perceived that the model was incomplete since it did not truly incorporate the IS research stream and their theories into its model. Thus, Bhattacherjee & Premkumar (2004) formulated a theory organized in two stages, pre-usage and usage. The first stage is structured as follows:

- Communication and other antecedents operate as external variables influencing Initial Beliefs.
- Initial Beliefs positively influence Initial Attitude.

Then, the actual use of the technology would happen, and the pre-usage phase would move into the usage phase, that is structured as follows:

- Initial Beliefs would positively, directly influence Satisfaction and Modified Beliefs.
- Initial Beliefs would negatively, directly influence Disconfirmation.
- Initial Attitude would positively, directly influence Modified Attitude.
- Disconfirmation would positively, directly influence Modified Beliefs and Satisfaction.
- Modified Beliefs and Satisfaction would positively, directly influence Modified Attitude.
- Modified Beliefs and Modified Attitude would positively, directly influence Modified Intention.

The results of the studies suggest that:

- Beliefs and Attitudes tend to change over time, although such fluctuations are more evident in the initial phases of technology acceptance. Thus, two evident consequences of such findings are that i) usage does influence beliefs and attitudes – and, hence, following usage; and ii) when the individual possess great experience with such technology its beliefs and attitudes tend to remain mode stable.
- Disconfirmation and Satisfaction are better predictors of Modified Beliefs and Attitudes than Initial Beliefs and Attitudes. Hence, reconfirming and adding to what it was written in the previous paragraph, "experimental" usage has overall a greater influence on long-term adoption of a technology.
- The variance of the new beliefs and attitudes unexplained by the factors used in this study may imply that new constructs should be added to this model. As an exploratory study, Bhattacherjee & Premkumar (2004) used only Perceived Usefulness (PU) as a belief since it is the most empirically validated construct in Information Systems research.

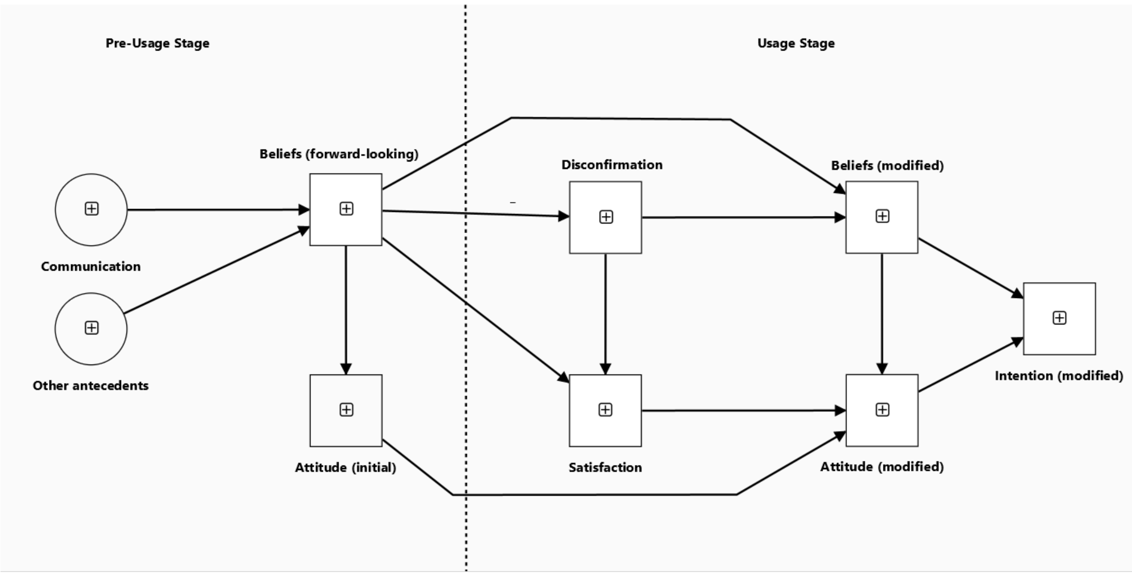

Figure 14: original two-stage model Bhattacherjee & Premkumar, 2004)

Part of the suggestions of the Bhattacherjee & Premkumar's (2004) model have been considered by some scholars and have amended the theory. One particularly relevant study for this research is Venkatesh et al. (2011), that operated two changes:

- Firstly, it included all the core constructs from the UTAUT model (Venkatesh et al., 2003) in the beliefs section, moving it from being only composed by PU, i.e. a precursor of PE, to having PU/PE, EE, SI, FC. For each concept the hypotheses as explained in Bhattacherjee & Premkumar (2004) have been empirically tested.

- Secondly, since the study focused on "transactional systems that involve transmission of personal and sensitive information" (Venkatesh et al., 2011, p. 527), the concept of "Trust" has been added to the beliefs – and empirically tested like the others.

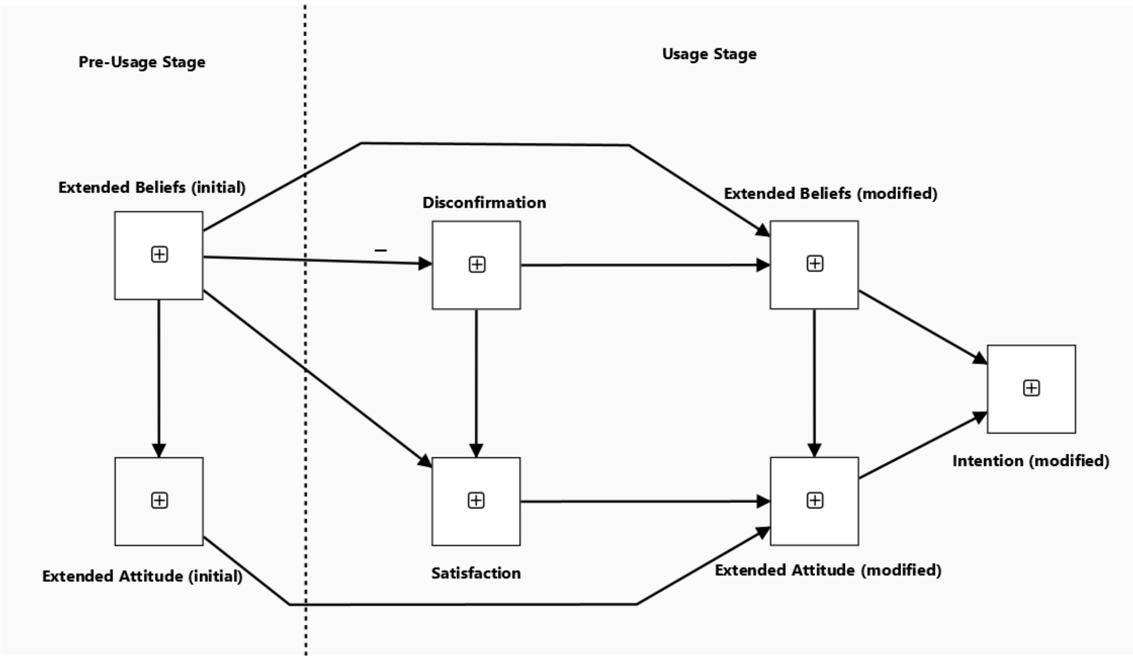

Figure 15: expanded two-stage model (from Venkatesh et al., 2011)

The findings confirmed the hypotheses formulated and contributed to the need of inserting context into IS research. As such, it suggested that other variables might be put into the development of a model to predict behavioral intention or actual use. Moreover, it implied that the original UTAUT's predictors can have a relationship with Attitude and Satisfaction, despite in that model such constructs have been excluded, respectively, after the empirical evaluation or *a priori* in the initial conceptualization.

3.2 Conceptual Change Models

This subsection explores a field that, at a first glance, does not appear to relate to the one previously developed, that is, technology adoption. However, part of the objective of this study is to find a way to integrate these two research literatures, so that a more precise model can be developed and validated.

The subsection is organized as follows: it introduces the first theory of conceptual change (Posner et al., 1982). Subsequently, it shifts the focus from the learning of the students to the learning of the teachers – not as training teacher, rather as teachers who must change their opinions on their teaching practice with the purpose of improving it (Gess-Newsome et al., 2003; Southerland et al., 2012; Woodbury & Gess-Newsome, 2002).

3.2.1 Toward a Theory of Conceptual Change in Education

This field of study is an attempt to answer the following question: "Under what conditions does one central concept come to be replaced by another?" (Posner et al., 1982, p. 213).

The preconception behind this idea relies on the statement for which learning occurs when there is an interaction between what the learner finds itself in front of and its already-existing concepts – thus, this view contrasts with traditional empiricism, for which an individual can learn an idea without any prior concepts.

Posner et al. (1982) derived the interest on the process of conceptual change from the field of philosophy of science – and introduced it into educational psychology. They build their model on two initial assumptions: the first one is that learning, in its essence, is a rational activity, and, hence, it is not just the acquisition of responses or behaviors; rather, it is a formulation of concepts – "ideas" (Posner et al., 1982, p. 212) – and their relationship with empirical evidence. The second one is explained after the following paragraph.

In their model, Posner et al. (1982) distinguish two phases of conceptual change applied to learning: in the first one, learners use already acquired concepts "to deal with new phenomena" (Posner et al., 1982, p. 212). This process is called *assimilation*. In the second phase, instead, the learner does not possess concepts capable of processing such novelties, and, thus, it needs to substitute or modify its concepts. This process is called *accommodation*[1].

The second assumption, hence, posits that the learner would always try to use its already developed conceptions to understand a new phenomenon. This process, as we have seen, can be successful or not, but what truly matters is the fact that it is always applied. The reason why it is always applied relies on the preconception explained in the first paragraph of this subsection: that learning occurs with the interaction of already existing conceptions with experience. This happens because such conceptions are the base from which the learner starts its learning experience – without them it would not be able to properly learn anything. Posner et al. (1982, p. 213) refers to these concepts as "conceptual ecology".

Thus, the idea of a *conceptual ecology* completes the initial question, that could be expressed also in the following way: how does *accommodation* takes place? Moreover, a new question arises: to do so, i.e., having an *accommodation*, "what are the features of a conceptual ecology which govern the selection of new concepts?" (Posner et al., 1982, p. 213).

[1] The terms *assimilation* and *accommodation* have been derived from Piaget (1929; 1930; 1974).

The answer to the first question is a list of four conditions that enhance the possibilities of conceptual change, and it is developed in the following statements (Posner et al., 1982, p. 214):

- "There must be dissatisfaction with existing conceptions": a learner will not accept such radical change unless it is convinced that it is necessary.
- "A new conception must be intelligible": if the structure of the new idea cannot be comprehended the individual will likely not adopt it.
- "A new conception must appear initially plausible": if the new conception cannot answer the need that its antecedents failed to, then it will most likely not be accepted.
- "A new concept should suggest the possibility of a fruitful research program": since this theory is derived from philosophy of science, it uses a terminology that focuses on scientists' thinking and behavior. However, "research program" refers to the general idea of extending a concept, opening to following inquiry.

The answer to the second question, instead, is another list of types of concepts that are determinants for an *accommodation* (Posner et al., 1982, p. 214-215):

- "Anomalies": the features of an existing idea's failure determine the choice on the successor.
- "Analogies and metaphors": such ideas enhance the chances of intelligibility of a novelty.
- "Epistemological commitments" are divided in two:
    - "Explanatory ideals": every topic has subject-related way of determining what is accountable as a successful explanation related to it.
    - "General views about the character of knowledge": contrary to the previous one, there are general standards to successfully occurring knowledge.
- "Metaphysical beliefs and concepts" are divided in two:
    - "Metaphysical beliefs about science" – again, Posner et al. (1982) focuses on scientists' conceptual change: beliefs on the rules the govern the universe so that it can influence the individual's scientific work.

- “Metaphysical concepts of science”: beliefs about the “ultimate nature of the universe [that…] are immune from direct empirical refutation”.

- “Other knowledge” – that again comprises two elements:
  - “Knowledge in other fields”.
  - “Competing concepts”: the novelty should appear more promising than its competitors.

This model, as explained so far, has had a certain influence on the field of educational technology: many others started realising that “beliefs can be […] the single most important construct in educational research” (Pajares, 1992, p. 329) – and, according to (Pajares, 1992), *belief* can be a reasonable substitute for *conception* as used in Posner et al. (1982).

3.2.2 The development of the construct of teachers’ beliefs

Pajares (1992, p. 324-326), attempting to better categorize the construct of teachers’ beliefs, provides a comprehensive list of “fundamental assumptions” on teachers' educational beliefs (here it is shown without its extended literature review, that can be found in the abovementioned pages):

1. “Beliefs are formed early and tend to self-perpetuate, persevering even against contradictions caused by reason, time, schooling, or experience”.
2. “Individuals develop a belief system that houses all the beliefs acquired through the process of cultural transmission”.
3. “The belief system has an adaptive function in helping individuals define and understand the world and themselves”.
4. “Knowledge and beliefs are inextricably intertwined, but the potent affective evaluative, and episodic nature of beliefs makes them a filter through which new phenomena are interpreted”.
5. “Thought processes may well be precursors to and creators of belief, but the filtering effect of belief structures ultimately screens, redefines, distorts, or reshapes subsequent thinking and information processing”.
6. “Epistemological beliefs play a key role in knowledge interpretation and cognitive monitoring”.

7. “Beliefs are prioritized according to their connections or relationship to other beliefs or other cognitive and affective structures. Apparent inconsistencies may be explained by exploring the functional connections and centrality of the beliefs”.

8. “Belief substructures, such as educational beliefs, must be understood in terms of their connections not only to each other but also to other, perhaps more central, beliefs in the system. Psychologists usually refer to these substructures as attitudes and values”.

9. “By their very nature and origin, some beliefs are more incontrovertible than others”.

10. “The earlier a belief is incorporated into the belief structure, the more difficult it is to alter. Newly acquired beliefs are most vulnerable to change”.

11. “Belief change during adulthood is a relatively rare phenomenon, the most common cause being a conversion from one authority to another or a gestalt shift. Individuals tend to hold on to beliefs based on incorrect or incomplete knowledge, even after scientifically correct explanations are presented to them”.

12. “Beliefs are instrumental in defining tasks and selecting the cognitive tools with which to interpret, plan, and make decisions regarding such tasks; hence, they play a critical role in defining behavior and organizing knowledge and information”.

13. “Beliefs strongly influence perception, but they can be an unreliable guide to the nature of reality”.

14. “Individuals' beliefs strongly affect their behavior”.

15. “Beliefs must be inferred, and this inference must take into account the congruence among individuals' belief statements, the intentionality to behave in a predisposed manner, and the behavior related to the belief in question”.

16. “Beliefs about teaching are well established by the time a student gets to college”.

Among these points, some of them emerge as relevant for this study:

I. Assumptions 1, 2, 3, 4, 5, 6, and 8 confirm the theory expressed in in Posner et al. (1982) about the importance of central conceptions and their function as base from which the individual learns – i.e., they confirm the existence of a *conceptual ecology*.

II. Assumptions 12, 13, and 14 confirm what stated in the technology acceptance research field, i.e., that beliefs influence perception and, thus, behavior.

III. Assumptions 1, 9, 10, 11 and 16 confirm the need of a research field examining the process for which an individual can modify its *conceptual ecology*, due to the difficulty to succeed in such changes and the complexity of such processes.

IV. Assumptions 7 and 8 suppose that there could be an interaction between technology adoption and educational psychology research: in fact, the idea that different beliefs can interact with each other and with deeper concepts corresponding to attitudes and values assumes the possibility of integrating technology acceptance models with elements from the theory of conceptual change.

3.2.3 The Teacher-Centered Systemic Reform (TCSR) model

Given the possible integration of IS adoption/UTAUT and conceptual change models (CCM), there is a need of explaining how such beliefs would interact in the context of school reforms. This has been introduced by Woodbury & Gess-Newsome (2002) with the TCSR model.

TCSR has been developed after a review of the school change literature stated that the previous attempts of school reform caused a “change without difference” (Woodbury & Gess-Newsome, 2002, p. 765), since their four main driving factors, namely systems, context, intention of the reform, and teacher thinking were incomplete without each other. Hence, TCSR is a combination of these four elements.

More precisely: systems refer to the intricated relationships among all the stakeholders involved – that, thus, combine for a wicked, confusing system. The cultural and structural context, similarly to systems, refers to the teaching environment, i.e., the relationship among colleagues and students, the grading system, but also the influences of the political and administrative structure of the country in which the school is – these two elements, evidently, are almost identical.

The third factor is the goal of the proposed reform: the idea is that such attempt to change the status quo would influence the type of results obtained, i.e., a reform that would try to improve the effectiveness of already-existing structures, processes, methods it intrinsically believes that such structures, processes, methods are correct; instead, a reform that would try to radically change the way in which an organization, or school, is composed and exists would imply that its way of thinking its structures, processes, methods is not correct.

Finally, teachers' thinking is the main driver of teachers' behavior – and as such it is the origin of the issues and the key for success. The relevant knowledge and beliefs are about: the subject content; students and learning; teachers and teaching – and their own teaching efficacy; change itself. Finally, all the previous factors are influenced by teachers' knowledge and beliefs about the objectives of the schools and institutions they are part of.

Thus, TCSR comprehends the general context of reform – divided into personal factors, such as demographic profile, preparation to teach, teaching experience, continued learning efforts; and contextual factors, such as national state and district context, school context, department and subject area context, classroom context – that, mediated by teachers' thinking on the elements previously described, would influence teachers' practice.

The findings of an empirical evaluation of TCSR resulted in highlighting teachers' perceptions of necessity of change and their knowledge of the subject taught as predominant predictors of teachers' responses to reform. Moreover, five factors resulted influencing their thinking about and their enacted change: "(a) a departmental culture of sharing, (b) teachers' sense of autonomy, (c) teachers' professional development experiences, (d) the nature of reform messages and messengers, and (e) teachers' views of themselves in relation to the reform movement" (Woodbury & Gess-Newsome, 2002, p. 777).

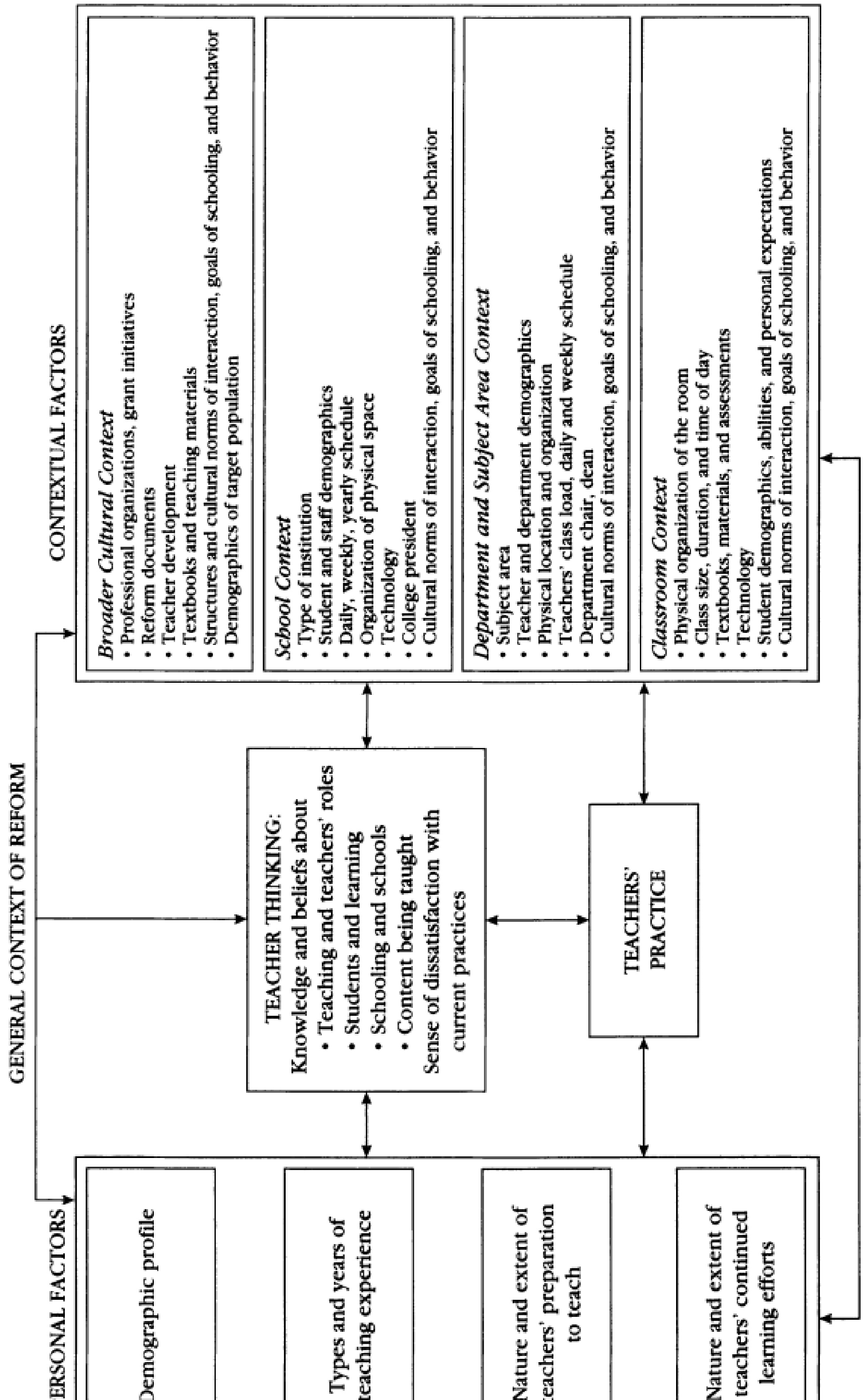

Figure 16: TCSR (from Woodbury & Gess-Newsome, 2002)

A following study's (Gess-Newsome et al., 2003) findings confirmed that teacher's dissatisfaction with its current objectives and practices, and its motivation to change are fundamental for reform's success – in fact, that study added the sense of dissatisfaction with the current practices in the teacher's thinking section of the TCSR. Moreover, it suggests that investments on mitigating cultural and structural constraints is a necessary, but not sufficient, influencing factor to foster change. Lastly, personal practical theories are the most influential predictors of teacher's practice. Thus, it can be stated that "the foundation of systemic change is individual change (Gess-Newsome et al., 2003, p. 763).

3.2.4 Pedagogical Discontentment

The centrality of this sense of dissatisfaction forced the scholars to focus on it and it resulted in the development of the construct of Pedagogical Discontentment (PD) (Southerland et al., 2011). As already mentioned in (Gess-Newsome et al., 2003), the concept of PD is different than contextual, general dissatisfaction: in fact, PD emerges when the teacher perceives a significant difference between its intended teaching goals and objectives, and its actual practice.

PD is later empirically evaluated on science teachers and expanded to comprise five subconstructs: the ability to teach all students science; science content knowledge; operating a balance between depth and breadth of instruction; implementation of inquiry instruction; assessment of science learning (Southerland et al., 2011).

The first subconstruct refers to the need to overcome the difficulties of realizing the learning objectives for students with different levels of studying abilities. In particular, teachers found themselves struggling with students with lower levels of studying abilities. It must be noted, however, that teachers identified mostly with students who had higher levels of studying abilities. Thus, it was easier for them to understand such students and deal with them.

The second subconstruct concerns the difficulty of explaining the exact level of content knowledge of each teacher's subject: indeed, all teachers have studied those topics way more in detail. However, knowing what level of details need to be explained to the students is not necessarily given – and such desired outcome requires a constant effort of controlling the theory, so that the teacher can ensure it can explain what it is supposed to explain.

The third subconstruct refers to the perceived limitations to autonomy felt by the teachers in their teaching activities. For instance, an external constraint could be national test standards, that influence the specific depth and breadth of the content taught by the teachers, since they force what exactly students should know and hence what teachers should explain.

The fourth subconstruct, very peculiar to science teaching, is the implementation of inquiry practices. The struggle, in this context, refers to the difficulty of applying such methods to day-to-day teaching: many teachers tried to adopt inquiry, but failure was almost inevitable – and hence, dissatisfaction emerged as the almost impossibility of succeeding in this process.

The fifth subconstruct reflects the complicatedness of evaluating the learning process from two perspectives: the first one concerns the determining why the actual output did or did not meet the expectations. In this category the wicked issue is the root-cause of the measurement used, i.e., whether such dimension measures teachers' or students' actions. The second perspective is about the communication of the measurement results – i.e., how such results can be interpreted by the students and their families. They might reject some evaluations because they do not understand the evaluation method, maybe considering it too hard or soft depending on the situation – thus, this could happen both with good and bad results.

Adding to the previous studies, Southerland et al. (2012) introduced a scale for measuring PD, with roughly the same subconstructs explained before. The scale is measured as a Likert scale of "the degree to which you [the teacher] are discontent of your practice concerning the following statements" and can be seen in the following table.

Subconstruct	**Item**
Implementing inquiry instruction (IB)	(1) Preparing students to assume new roles as learners within inquiry-based learning.
	(2) Using inquiry-based teaching within all content areas.
	(3) Assessing students' understandings from inquiry-based learning.
	(4) Assessing students' nature of science understanding.
	(5) Ability to plan successful inquiry-based activities/learning.
	(6) Teaching science to students of lower ability levels.

Ability to teach all students science (AL)	(7) Orchestrating a balance between the needs of both high and low ability-level students.
	(8) Including all ability levels during inquiry-based teaching and learning.
	(9) Teaching science to students from economically disadvantaged backgrounds
Science content knowledge (SC)	(10) Having sufficient science content knowledge to generate lessons.
	(11) Teaching science to students of higher ability levels.
	(12) Teaching science subject matter that is unfamiliar to me.
	(13) Having sufficient science content knowledge to facilitate classroom discussions.
Balance depth versus breadth of instruction (DB)	(14) Balancing personal science teaching goals with those of state and national standards.
	(15) Balancing personal science teaching goals with state/national testing requirements.
	(16) Balancing the depth versus breadth of science content being taught.
Teaching nature of science (TN)	(17) Assessing students' nature of science understanding.
	(18) Integrating nature of science throughout the curriculum.
	(19) Developing strategies to teach nature of science.
Assessing science learning (AP)	(20) Monitoring student understanding through alternative forms of assessment.
	(21) Planning and using alternative methods of assessment.

	(22) Using assessment practices to modify science teaching.

Table 1: STPD items (from Southerland et al., 2012)

Besides the subconstructs explained above, Southerland et al. (2012) introduces the teaching of the nature of science – that fulfils the purpose of introducing the students to the way of thinking and of practicing science. However, besides adding more precision to the concept of dissatisfaction, Southerland et al. (2010; 2011; 2012) contribute to the conceptual change literature also by confirming, once again after Posner et al. (1982), Pajares (1992), and Gess-Newsome et al. (2003), that dissatisfaction contributes to change only when it is combined with self-efficacy, i.e., with the individual's belief that it possesses sufficient skills and knowledge to succeed in that changing process.

3.3 Artificial Intelligence in the Public Sector (AI-PS)

The idea of the public sector being the end user of AI technology is oftentimes overlooked (Medaglia et al., 2021): in fact, governments, especially within the European context, are mostly focused on industrial opportunities or reducing societal threats (Guenduez & Mettler, 2022). However, adopting such technologies is mandatory for governments since the expectations on the improvements of public services are high – maybe even too high (Sienkiewicz & Malyjurek, 2023).

A few years ago, de Sousa et al. (2019), analyzing the state of the research, concluded that it remained mostly unknown what are the factors that influence the usage of AI technology, and what the consequences would be. In the following years, the literature has tried to fill this gap by using both normative and empirical studies with different frameworks and perspectives (see below).

For instance, researchers have found that in practical situations most attempts to succeed in AI adoption did not have articulated strategic plans behind (Sienkiewicz & Malyjurek, 2023), were lacking sufficient financial resources (Rjab et al., 2023) and resulted in occasional adoptions rather than a continuous deployment (Real & Poole, 2004) – ironically, some practitioners even considered the overcome of some barriers to adoption as successful adoption cases (Kuguoglu et al., 2021).

The importance of continuous efforts does not involve only AI. Rather, it is in direct relationship with digitalization: previous efforts on this regard have been found to be necessary to a successful AI deployment (van Noordt & Misuraca, 2022; Agarwal, 2018). This happens for two reasons that influence each other: first, because AI systems should not be handled separately from the information systems that already exist; second, because AI-in-government trade-offs are layered upon digital-in-government trade-offs –

i.e., the choices that public sector designers make on AI services must be traced on the choices made on the digital services (Kuguoglu et al., 2021).

Indeed, the importance of the context must be mentioned: the environment should produce an *ad hoc* regulation and foster the competition for the development of such technologies; the organization should provide coordination among the processes and senior management support; the technology required for AI adoption concerns ICT infrastructure, data security and ICT expertise (Sienkiewicz & Malyjurek, 2023).

Regarding expertise, public sector employees and managers have been oftentimes considered without sufficient AI-related skills (Mikalef et al., 2021; Wirtz et al., 2019), knowledge (Sienkiewicz & Malyjurek, 2023), and understanding (Neumann et al., 2022; Rjab et al., 2023) – situations that, subsequently, limit the adoption and the performance of such tools (Herd & Moynihan, 2019). Thus, training programs appear to be a requirement in such scenario (Ahn & Chen, 2021) – especially since the importance of local networks (van Noordt & Misuraca, 2022) and their openness towards innovation (McLeay et al., 2021) have been addressed.

Another need is for more explainability of AI compared to other ICTs. This is given by the complexity of its behavior (Sun & Medaglia, 2019). In this sense, "explainable" is a technology capable of providing an explanation for its decision-making process (Gunning et al., 2019). The general lack of explainability in AI-PS technologies has been addressed numerous times (de Bruijn et al, 2021; Janssen et al., 2020; Rjab et al., 2023).

The main consequence of absence of explainability is lack of trust (Grimmelikhuijsen, 2022), especially in AI-PS since it could undermine the legitimacy of public institutions (van Noordt & Misuraca, 2022). A solution to this issue is the introduction of a responsible actor behind AI-PS decisions (Sun & Medaglia, 2019). This proposal of ensuring accountability should also overcome any transparency-related problem (de Bruijn et al., 2022; Chen et al., 2023; Schiff et al., 2021).

3.4 Artificial Intelligence in Education (AIED)

Education is indeed a field of public interest. Yet, it is oftentimes overlooked (European Commission, 2020). The four main areas of AIED are i) profiling and prediction; ii) assessment and evaluation; iii) adaptive system and personalization; iv) intelligent tutoring system (Zawacki-Richter et al., 2019).

The first point refers the possibility of foretelling learning status, performance or satisfaction (Ouyang et al., 2022) that the students will obtain or feel based on previous records (Chen et al., 2022). The term often used for such activity is "precision education"

(Yang et al., 2021). Such results can be achieved through the use of sensors or wearable devices (Ciolacu et al., 2018).

The second point concerns the evaluation of students' activities. AIED is supposed to increase effectiveness and efficiency (Chen et al., 2020a), since it is useful to reduce workloads (Rudolph et al., 2023). The use of automation (Ouyang et al., 2022; Yang et al., 2021) and neural networks (Chen et al., 2022) is recommended for such purpose.

The third element is probably the most cited one and concerns the possibility of shifting from a single teaching method for all the students to a more individual path for learning success (Roll & Wylie, 2016). This can be obtained by observing the students' preferences (Hwang et al., 2020), needs (Chen et al., 2020b) – that can change through the grades or being fixed due to, for instance, individual disabilities (Kasneci et al., 2023). It could give the student the possibility to learn in a more self-paced way (Yang et al., 2021) or to achieve the desired learning outcome through an individual digital recommender system (Ouyang et al., 2022).

Personalization is strongly correlated with the fourth and last point, intelligent tutoring systems (ITSs), i.e., AI applications (Ouyang et al., 2022) that "provide cost-effective instruction" (Chen et al., 2020b, p. 15) by substituting the on-on-one human tutor (Roll & Wylie, 2016) for distant education or for learners with disabilities (Kasneci et al., 2023).

The main challenge of smart tutors concerns humans' agency (Hwang et al., 2020): if, on the one hand, ITSs objective is to empower students in their learning path (Ouyang & Jiao, 2021), on the other hand such technology can limit teacher's agency: firstly, the use of AIED leaves teachers primarily only the role of curriculum designers (Zhai et al., 2021), since it can almost substitute them in the abovementioned points; secondly, the use of AI tools by the students to perform some tasks could fool teachers into not being able to determine whether such outputs are the result of human's or machine's activity.

Such possibility leads to think that "if a machine is capable of outwitting a teacher's pedagogy, it may be able to replace the teacher" (Rudolph et al., 2023, p. 353). This fear of replacement is well present in general in AI-PS literature (for instance, see Wirtz, 2019) and it concerns the need for trust in both government and AI when implementing such solutions into a publicly relevant system (Rudolph et al., 2023).

The identified solution by the literature, when concerning education, is fostering AI literacy (Kandlhofer et al., 2016). AI literacy is built on four aspects: the individual is supposed to be able to i) know and understand AI concepts; ii) use and apply AI tools;

iii) evaluate and create AI solutions; iv) understand the ethical issues behind the use of AI (Ng et al., 2021).

Another issue is the lack of connection in the literature between AI characteristics and pedagogical strategies (Zawacki-Richter et al., 2019), that indicate an evident missing of a clear strategy (Kasneci et al., 2023). Most of the literature, then, focused on the development of frameworks (Hwang et al., 2020; Zhai et al., 2021) or the identification of paradigms (Ouyang & Jiao, 2021). AI, however, if connected to a proper use in education is expected to substantially improve the quality of teaching outcomes through the areas explained so far (Chen et al., 2020a; Holmes et al., 2022; Ouyang et al., 2022; Rudolph et al., 2023).

3.5 The Italian administrative and educational school system

Italy is a unitary state, yet its administrative system does not give all the powers and responsibilities to its National Ministry of Education: The Constitutional Law 3/2001 (that is, constitutional law number 3 of the year 2001) implement a federalist reform of the country and recognizes the same importance of Regions and Municipalities with the State.

Regarding the education system, the 2001 reform and some other laws divide the legislative power between State and Regions. The exclusive competence of the State concerns i) the general norms of education; ii) the essential level of performances; iii) the fundamental principles to which concurrent legislation of Regions must be inspired to.

The first point, according to the sentence 200/2009 of the Constitutional Court, comprehends:

- the establishment of schools for all levels and grades.
- the right of organisations and private individuals to establish schools and educational establishments at no cost to the state.
- parity between state and non-state schools in terms of their full freedom and equal treatment of pupils.
- the necessity of a state examination for admission to or completion of the various school levels and grades.
- the openness of schools to all.
- the compulsory and free nature of lower education.

- the right of able and deserving pupils, even if without means, to reach the highest grades of studies.
- the need to make the right referred to in the preceding point effective by means of scholarships, family allowances and other provisions, to be allocated by competition.

The second point concerns the civil and social rights to be guaranteed on all the national territory. The third point, instead of the first one, refers to practical indications that set objectives, criteria and standards of procedures that, to exist, must be practically put into action by the regional offices. These concern, for instance, the continuing education of teachers, the monitoring of the evaluation of the performances of the students, the update of the data protection law concerning the school system, etc. The Regions, instead, are responsible for managing the resources, relatively to their territory, assigned to them by the Ministry of Education. They also are responsible for determining the details of the yearly school calendar for the schools belonging to them.

Concerning the school-State relationship, the schools have autonomy on educational planning, organizational planning, and on research, experiments and development. This has been declared by the DPR 275/1999 ("Decree of the President of the Republic"), so that teachers could have better autonomy to articulate their educational offers in the specific context they operate.

However, such autonomy must be analyzed on the lens of the national dispositions, i.e., on the residual autonomy given after a national decision on what are the standards. For instance, the school system is organized as such: before university, or tertiary education, there is a pre-school period, that goes until the kids are 6-year-old. When they turn 6, they go to primary school, that comprehends the grades from 1 to 5 (thus 6 to 10 years old), in which all the subjects are decided on a national level, although each school could decide whether to add new subjects to the educational curriculum.

There is a secondary inferior school (often referred to as "middle school"), comprehending grades 6 to 8 (11 to 13 years), in which most of the subjects of the curriculum are decided on a national level. However, each school could decide which languages put as "second foreign language" in their offer – stating that English is the main foreign language.

Subsequently, there is secondary superior school, or simply "secondary school", that concerns grades 9 to 13 (14 to 18 years), at which beginning the students choose among three general options – *Liceo, Istituto Tecnico, Istituto Professionale*.

The first one proposes various paths to the students, leading them to tertiary education: they range from humanities to social sciences, from artistic to scientific curricula. The second and the third types of school are intended to offer, respectively, a technical and a professional education, in which the objective is to prepare students to face the job market at the end of their path.

Thus, students start choosing more personalized paths decided by the teachers only from grade 9 onwards. Indeed, teachers’ agency on the curricula is limited by the national guidelines. However, it is sufficient to open to different forms of evaluation, teaching, student engagement. The amount of path possibilities makes the grades 9-13 to most interesting to be researched and this is why that section of the Italian school system is the one chosen as relevant for this study.

4 Hypotheses formulation and model proposal

In this chapter, all elements explored in the literature review are combined to create the model through the hypotheses that will be tested empirically, as it is explained in the Methodology section.

4.1 Predictors

4.1.1 Performance Expectancy

Since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Performance Expectancy (PE) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on both Attitude (AT) – TRA, TPB, TAM, TAM2, DTPB, C-TAM-TPB, SCT, AT-UTAUT, Original two-stage, Extended two-stage – and Behavioral Intention (BI) – MPCU, IDT, SCT, UTAUT, AT-UTAUT, IS Continuance, Original two-stage, Extended two-stage. As such:

- *Hypothesis 1a) Performance Expectancy directly, positively influences Attitude*[2].
- *Hypothesis 1b) Performance Expectancy directly, positively influences Behavioral Intention.*

4.1.2 Effort Expectancy

Similarly to PE, since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Effort Expectancy (EE) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on both Attitude (AT) – TRA, TPB, TAM, TAM2, DTPB, C-TAM-TPB, AT-UTAUT, Extended two-stage – and Behavioral Intention (BI) – MPCU, IDT, UTAUT, AT-UTAUT, IS Continuance, Extended two-stage. As such:

- *Hypothesis 2a) Effort Expectancy directly, positively influences Attitude*[3].
- *Hypothesis 2b) Effort Expectancy directly, positively influences Behavioral Intention.*

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[2] Thus, as it will be seen, PE influences BI also through the mediation of AT. Implications will be explained in the discussion section.

[3] Thus, as it will be seen, EE influences BI also through the mediation of AT. Implications will be explained in the discussion section.

4.1.3 Social Influence

Similarly to PE and EE, since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Social Influence (SI) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on both Attitude (AT) – TAM2, AT-UTAUT, Extended two-stage – and Behavioral Intention (BI) – TRA, TPB, DTPB, C-TAM-TPB, MPCU, IDT, UTAUT, AT-UTAUT, Extended two-stage. As such:

- *Hypothesis 3a) Social Influence directly, positively influences Attitude.*
- *Hypothesis 3b) Social Influence directly, positively influences Behavioral Intention.*

4.1.4 Facilitating Conditions

Similarly to PE, EE, SI, since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Facilitating Conditions (FC) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on both Behavioral Intention (BI) – DTPB, MPCU, AT-UTAUT, Extended two-stage – and Usage Behavior (UB) – UTAUT, AT-UTAUT. As such:

- *Hypothesis 4a) Facilitating Conditions directly, positively influence Behavioral Intention.*
- *Hypothesis 4b) Facilitating Conditions directly, positively influence Usage Behavior.*

Finally, it must be noted that, as FC is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453), there are different types of support to enhance such use. Among them, there is Training. This construct has been found, in the context of technology education, to be a predictor of EE from teachers' side (Alshare & Lane, 2011). As such:

- *Hypothesis 4c) Facilitating Conditions directly, positively influence Effort Expectancy.*

4.1.5 Attitude

Similarly to PE, EE, SI, FC, since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Attitude (AT) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on both Behavioral Intention (BI) – TRA, TPB, TAM, TAM2, DTPB, C-TAM-TPB, MPCU, AT-UTAUT, Original two-stage, Extended two-stage – and Usage Behavior (UB) – SCT, AT-UTAUT. As such:

- *Hypothesis 5a) Attitude directly, positively influences Behavioral Intention.*
- *Hypothesis 5b) Attitude directly, positively influences Usage Behavior.*

4.1.6 Behavioral Intention

Similarly to PE, EE, SI, FC, AT, since the model proposed in this study is based on the reconceptualization of UTAUT as described by Dwivedi et al. (2019), Behavioral Intention (BI) is expected to be a valuable and significant predictor. The construct follows the literature concerning its and its roots' influence on Usage Behavior (UB) – TRA, TPB, TAM, TAM2, DTPB, C-TAM-TPB, UTAUT, AT-UTAUT. As such:

- *Hypothesis 6) Behavioral Intention directly, positively influences Usage Behavior.*

4.1.7 Personal Innovativeness

Personal Innovativeness (PIN) is the first predictor of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, PIN is one of the most frequently added variables to the UTAUT model (Dwivedi et al., 2011; Venkatesh et al. (2016), and openness towards innovation is necessary to obtain AI-PS adoption (McLeay et al., 2021). As such:

- *Hypothesis 7a) Personal Innovativeness directly, positively influences Attitude.*
- *Hypothesis 7b) Personal Innovativeness directly, positively influences Behavioral Intention.*

4.1.8 Digital Use

Similarly to PIN, Digital Use (DU) is a predictor of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, in the AI-PS literature, the importance of previous innovation efforts is highlighted: notably, without previous digitalization adoption, there is no AI adoption (van Noordt & Misuraca, 2022). Moreover, both the original (Bhattacherjee & Premkumar, 2004) and the extended (Venkatesh et al., 2011) two-stage IS acceptance models underlined the importance of differentiating between a situation in which adoption does not occur and a situation in which adoption does occur. Their analysis is longitudinal – which means that they interview the same sample before and after adoption. In our study, that is cross-sectional (see methodology), we use the setting of this model to distinguish the current users from the non-users. As such, in this study we hypothesize:

- *Hypothesis 8a) Digital Use directly, positively influences Behavioral Intention.*
- *Hypothesis 8b) Digital Use directly, positively influences Usage Behavior*

4.1.9 Pedagogical Discontentment

Similarly to PIN and DU, Pedagogical Discontentment (PD) is a predictor of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, the Conceptual Change Model (CCM) literature has clearly demonstrated that the perceived need to change – in this case, to adoption, i.e., a form of change – is required to make that conceptual, and then behavioral, change happen (Gess-Newsome et al., 2003; Gregoire, 2003; Posner et al., 1982; Southerland et al., 2012; Woodbury & Gess-Newsome, 2002). As such:

- *Hypothesis 9a) Pedagogical Discontentment directly, positively influences Behavioral Intention.*
- *Hypothesis 9b) Pedagogical Discontentment directly, positively influences Usage Behavior*

4.1.10 Self-Efficacy

Similarly to PIN, DU, and PD, Self-Efficacy (SE) is a predictor of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, SE is one of the most frequently added variables to the UTAUT model (Dwivedi et al., 2011; Venkatesh et al. (2016). In the original model, SE was found non-significant in directly influencing intention and use because its effect was captured by EE (Venkatesh et al., 2003). Thus, in this study we include SE as an external variable, since the literature has stated that this can be its role in the model: in fact, SE is a precursor to Personal Innovativeness (Chell & Athayde, 2009), Effort Expectancy

(Brown et al., 2010), and Performance Expectancy (Compeau & Higgins, 1995a, 1995b[4]). As such:

- *Hypothesis 10a) Self-Efficacy directly, positively influences Performance Expectancy.*
- *Hypothesis 10b) Self-Efficacy directly, positively influences Effort Expectancy.*
- *Hypothesis 10c) Self-Efficacy directly, positively influences Personal Innovativeness.*

4.2 Moderators

4.2.1 Age

Age is a moderator used in the original UTAUT model (Venkatesh et al., 2003). In there, it is supposed to moderate the influences of all the original UTAUT predictors – PE, EE, SI to BI; and FC to UB. Moreover, it is also used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). As such, we hypothesize what follows:

- *Hypothesis 11a) Age moderates the influence of Performance Expectancy on Behavioral Intention.*
- *Hypothesis 11b) Age moderates the influence of Effort Expectancy on Behavioral Intention.*
- *Hypothesis 11c) Age moderates the influence of Social Influence on Behavioral Intention.*
- *Hypothesis 11d) Age moderates the influence of Facilitating Conditions on Behavioral Intention.*
- *Hypothesis 11e) Age moderates the influence of Pedagogical Discontentment on Behavioral Intention.*

[4] : Compeau & Higgins's papers also stated that SE influences directly some constructs that in our model would correspond to AT, BI, and UB. However, as already mentioned, Venkatesh et al. (2003) removed the possibility of SE to directly influence BI or UB; concerning AT, all the variables that are supposed to be influenced by SE are also supposed to influence directly AT. Thus, the hypotheses suggest that SE influences AT only when mediated by PE, EE, PIN – and the same goes for BI.

- *Hypothesis 11f) Age moderates the influence of Facilitating Conditions on Usage Behavior.*

- *Hypothesis 11g) Age moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.2 Gender

Gender is a moderator used in the original UTAUT model (Venkatesh et al., 2003). In there, it is supposed to moderate the influences of almost all the original UTAUT predictors – PE, EE, SI to BI. Moreover, it is also used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). As such, we hypothesize what follows:

- *Hypothesis 12a) Gender moderates the influence of Performance Expectancy on Behavioral Intention.*

- *Hypothesis 12b) Gender moderates the influence of Effort Expectancy on Behavioral Intention.*

- *Hypothesis 12c) Gender moderates the influence of Social Influence on Behavioral Intention.*

- *Hypothesis 12d) Gender moderates the influence of Pedagogical Discontentment on Behavioral Intention.*

- *Hypothesis 12e) Gender moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.3 Experience

Experience is a moderator used in the original UTAUT model (Venkatesh et al., 2003). In there, it is supposed to moderate the influences of almost all the original UTAUT predictors – EE, SI to BI; FC to UB. Moreover, it is also used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). As such, we hypothesize what follows:

- *Hypothesis 13a) Experience moderates the influence of Effort Expectancy on Behavioral Intention.*

- *Hypothesis 13b) Experience moderates the influence of Social Influence on Behavioral Intention.*

- *Hypothesis 13c) Experience moderates the influence of Facilitating Conditions on Behavioral Intention.*

- *Hypothesis 13d) Experience moderates the influence of Pedagogical Discontentment on Behavioral Intention.*

- *Hypothesis 13e) Experience moderates the influence of Facilitating Conditions on Usage Behavior.*

- *Hypothesis 13f) Experience moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.4 Years of teaching experience

Years of teaching experience (YearsXP) is a moderator of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, it is used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). As such, we hypothesize what follows:

- *Hypothesis 14a) YearsXP moderates the influence of Pedagogical Discontentment on Behavioral Intention.*

- *Hypothesis 14b) YearsXP moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.5 Experience in public vs private school

The public vs private school teaching experience is a moderator that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, it is used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). We subdivided it into "overall public-school experience" (PubXP), "overall private-school experience" (PriXP), "percentage of the experience in the public school on the total experience" (Pub/TotXP), "percentage of the experience in the private school on the total experience" (Pri/TotXP). As such, we hypothesize what follows:

- *Hypothesis 15a) PubXP moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 15b) PubXP moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 15c) PriXP moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 15d) PriXP moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 15e) Pub/TotXP moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 15f) Pub/TotXP moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 15g) Pri/TotXP moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 15h) Pri/TotXP moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.6 Subject experience

Subject experience is a moderator of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, it is used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher’s practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). For this study it has been subdivided in Humanities, Social Sciences, STEM. As such, we hypothesize what follows:

- *Hypothesis 16a) Humanities moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 16b) Humanities moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 16c) Social Sciences moderates the influence of Pedagogical Discontentment on Behavioral Intention.*

- *Hypothesis 16d) Social Sciences moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 16e) STEM moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 16f) STEM moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.2.7 Type of school experience

Type of school experience is a moderator of this model that is not included in the original UTAUT (Venkatesh et al., 2003), nor in its reconceptualization (Dwivedi et al., 2019). However, it is used in the TCSR model (Woodbury & Gess-Newsome, 2002) to influence teacher's practice with pedagogic dissatisfaction – elaborated here as Pedagogical Discontentment (PD). For this study it has been subdivided in *Liceo*, *Istituto Tecnico* [abbr. *"Tecnico"*], *Istituto Professionale* [abbr. *"Professionale"*],. As such, we hypothesize what follows:

- *Hypothesis 17a) Liceo moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 17b) Liceo moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 17c) Tecnico moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 17d) Tecnico moderates the influence of Pedagogical Discontentment on Usage Behavior.*
- *Hypothesis 17e) Professionale moderates the influence of Pedagogical Discontentment on Behavioral Intention.*
- *Hypothesis 17f) Professionale moderates the influence of Pedagogical Discontentment on Usage Behavior.*

4.3 Proposed model

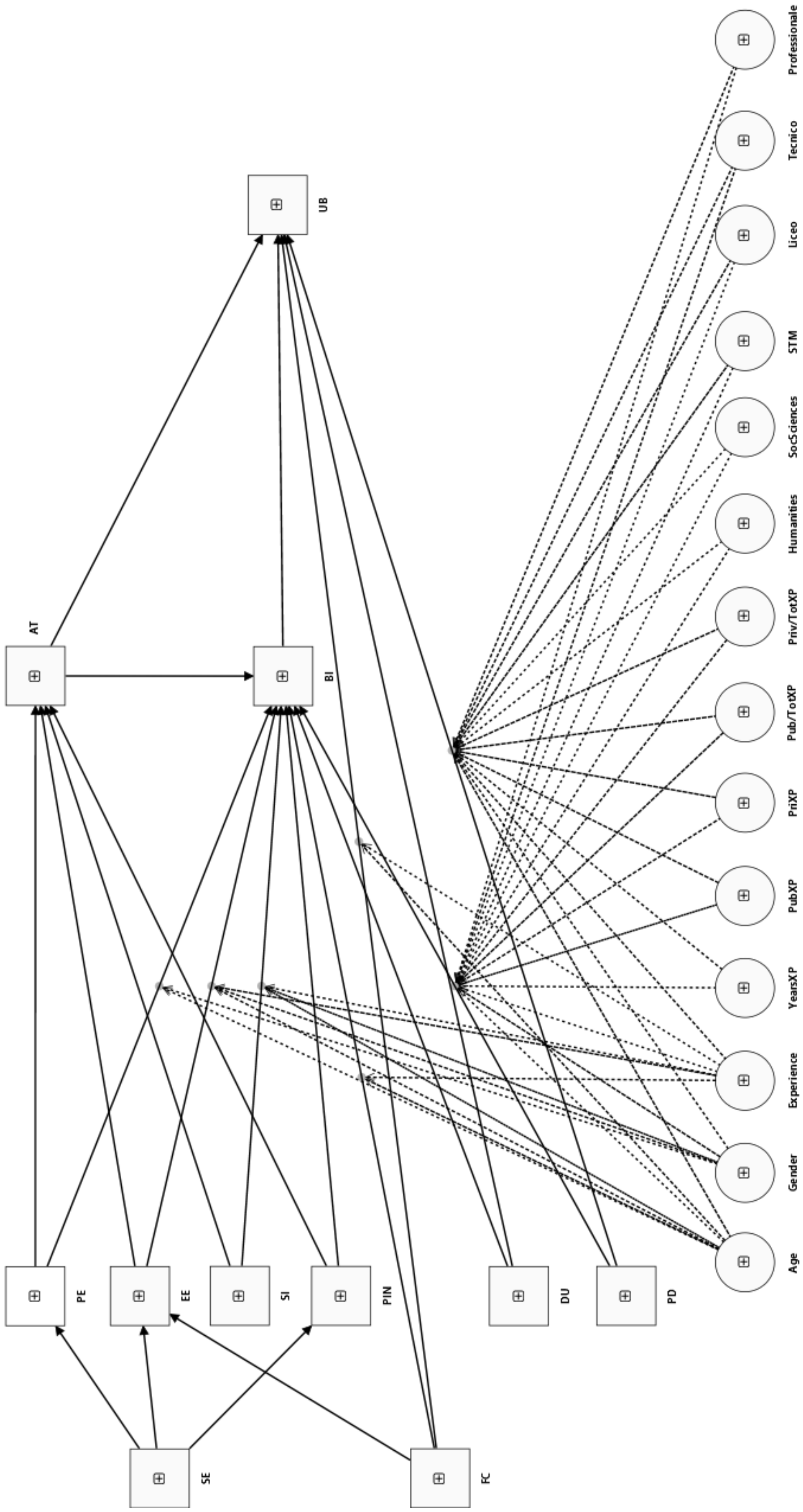

Figure 17: the proposed model

5 Methodology

The following section will outline the employed methodology. It will do so by presenting the Research Design, that is, a survey. Then it will list the features of such survey. Thirdly, it will show the data analysis procedure. Finally, it will list the limitations.

5.1 Research Design

Although there is only one research question, this study has both explanatory and exploratory ambitions. The explanatory part is the one concerns the hypotheses that have been confirmed by prior research as described in the literature section (cf. supra). Among these there are the ones approved by the UTAUT model as re-examined by Dwivedi et al. (2019), in which i) PE, EE, SI, FC, and AT directly influence BI – that also means, BI mediates their influence on UB; ii) PE, EE, SI directly influence AT – that also means, AT mediates their influence on BI; iii) AT, BI, and FC directly influence UB. Moreover, it includes the hypotheses regarding PIN influencing BI and AT (Patil et al., 2020), and all the moderators from Venkatesh et al. (2003).

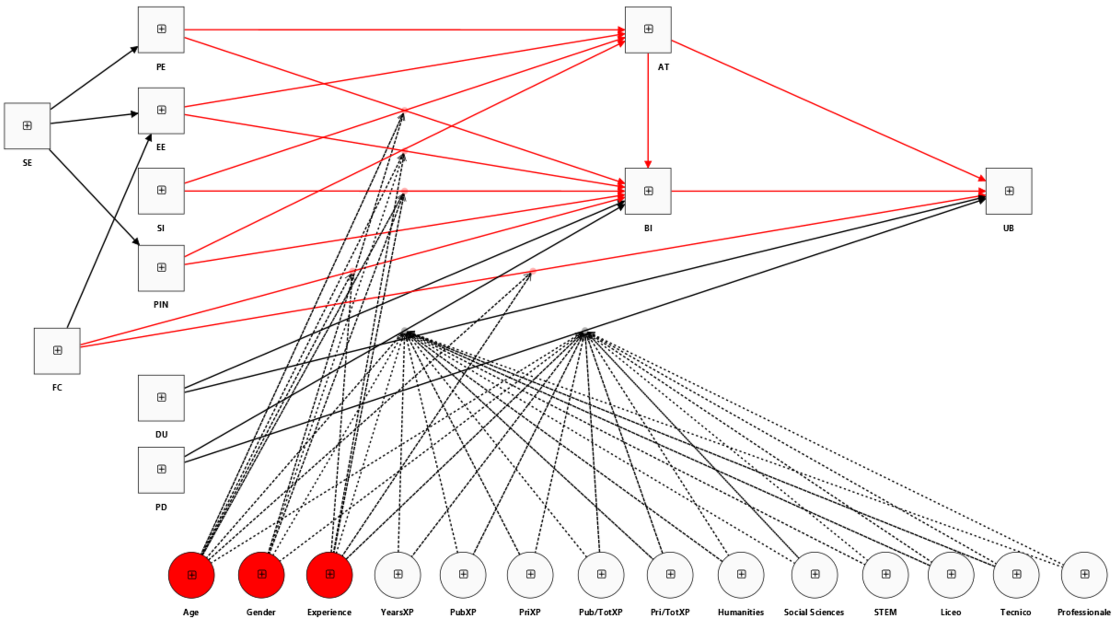

Figure 18: explanatory part of the proposed model (in red)

The exploratory section, instead, focuses on the parts of the model that are firstly conceptualized in this study – in this case "firstly" refers to the exact combination of hypotheses derived from a construct. For instance, SE has already been widely used in the literature, but not exactly as in this study. The exploring parts are: i) SE influencing PE, EE, PIN, (Brown et al., 2010; Chell & Athayde, 2009; Njiku et al., 2019); ii) the introduction of PD and its influence on BI and UB (Southerland et al., 2011; Venkatesh et al., 2011; Woodbury & Gess-Newsome, 2002); iii) the introduction of DU and its influence on and BI and UB (van Noordt, & Tangi, 2023); iv) the addition of FC to EE (Alshare &Lane, 2011).

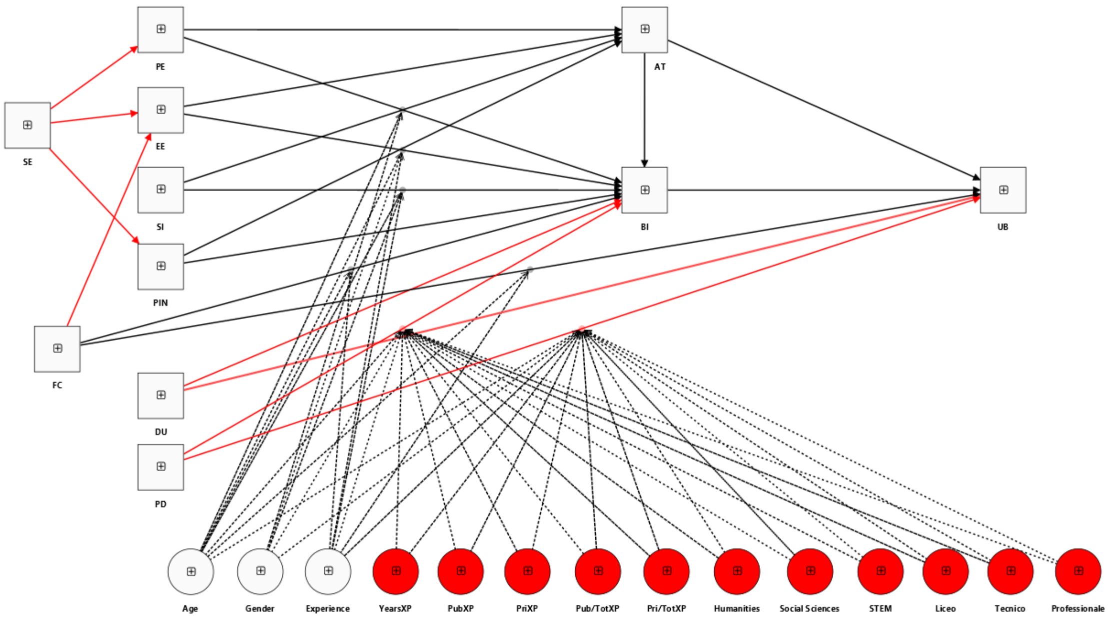

Figure 19: exploratory part of the proposed model (in red)

Concerning the proper method, it is applied a cross-sectional survey of the target population. The results are analyzed using Partial Least Square Structural Equations Modelling (PLS-SEM) regression to test the predictions made by the above-mentioned variation of the UTAUT model.

The results are critically discussed in the light of pertinent primary and secondary academic literature on AI adoption in the public sector and in education.

5.2 The survey

5.2.1 Target population

The target population (Wu & Thompson, 2020, p.10) are (1) teachers (2) working in Grades 9 to 13 of the Italian secondary education system, i.e., the *Scuola Superiore* ("High School"), (3) in the *Città Metropolitana di Torino* (i.e., Municipality of Turin and its surroundings).

These three elements are necessary because:

1. The analysis is about teachers' acceptance to use AI for teaching.

2. In the Italian school system, that is divided into Elementary (1-5 grades), Middle (6-8), High (9-13) School, only the latter – i.e., the one considered for this research – presents numerous types of schools with different subjects taught, and thus requires the students and their families to carefully consider to which one to apply in particular (see chapter on Italian school system).

3. The administrative area used for the study is composed of roughly 1,5 million total inhabitants and 107 schools, corresponding to some tens of thousands of teachers[5]. Thus, it represents a sufficient sample to be interviewed – even considering possible low respondent rates on the total of the population.

5.2.2 Data Collection

5.2.2.1 Sample

The list of the schools of the selected area has been retrieved on a platform sponsored by the website of the Italian Ministry of Education, in which all the schools of the country appear with their e-mail address (Ministero dell'Istruzione e del Merito, n.d.).

Of the 107 schools contacted via e-mail, 6 answered, providing a total of 768 possible survey respondents.

The low rate of answers received by the schools may be caused by some internal communication issues within the schools, since the e-mail retrieved belonged to the administrative offices rather than school leaders, pedagogy offices or teachers.

5.2.2.2 Mode of data collection

The fielding period corresponds to April and May 2024. The schools were contacted through multiple e-mails sent to their administrative offices, since their addresses were the only ones appearing in the Italian Ministry's website, as previously mentioned.

The platform used for the survey is LimeSurvey (Limesurvey, n.d.). Surveys hosted on LimeSurvey can be accessed from all conventionally used desktop computers and mobile devices. The selection bias introduced by limiting this survey to an online form is expected to be irrelevant, as all teachers have a school-related e-mail address. No incentives have been proposed to the responders.

[5] The actual number is not public. Thus, it will be considered, as the definitive total, the number of teachers working for the schools that answers to the e-mails.

5.2.2.3 Operationalization

The model variables were operationalized as latent variables, respectively measured indirectly through a set of indicators in the conducted survey. This operationalization of the dependant, independent and moderating model variables in the amended UTAUT framework was in large parts based on their respective operationalization in the above-mentioned existing research (for the complete questionnaire, see Appendix A). More specifically:

i. The independent and dependent variables developed in the original UTAUT model (Venkatesh et al., 2003), namely PE, EE, SI, FC, BI, were either simply adapted to the context of this study or combined with other literature so that those specific items could better represent the possible challenges or issues pointed out by the field of the research.

ii. DU and UB has been framed similarly: DU, in fact, is the UB of a previous technology of AI. Thus, they have been both operationalized using the UTAUT2 original paper as a model (Venkatesh et al., 2012).

iii. PIN has been adapted from Agarwal & Prasad (1998).

iv. SE has been derived from what Ng et al. (2021) list as the different degrees of AI literacy, i.e., AI knowledge, AI usage skills, AI analytics/evaluation, and the comprehension of the following ethical issues. Thus, AI Self-Efficacy is here intended as the self-reported degree of possession of what the literature has stated to be AI literacy.

v. PD is introduced in this study as the intersection of AI adoption literature, continuance of adoption model (Bhattacherjee & Premkumar, 2004; Venkatesh et al., 2011), and the educational psychology of the models of conceptual change literature (Southerland et al, 2011; Woodbury & Gess-Newsome, 2002). Hence, its items' structure is adapted from Vila & Kuster (2011); the meaning is derived from Southerland et al. (2011); the context from numerous articles, such as Kasneci et al. (2023), Chen et al. (2020), Zawacki-Richter et al. (2019).

vi. AT did require some specific consideration: despite the definition found in Fishbein & Ajzen (1975) – "an individual's positive or negative feeling about performing the target behavior" (p. 216) – the literature has vastly conceptualized this construct using not only its affective component, that is, the "feeling", but also some behavioral and cognitive meaning (Njiku et al., 2019). Thus, a literature review on the topic of teachers' attitudes on AI in education has been performed and it has suggested that the main challenges, issues, and drivers to AI adoption – that do not belong to other constructs included in the model – concerns teachers' agency (Nazaretski et al., 2022), the possibility of AI substituting teachers (Hwang et al., 2020; Rudolph et al., 2023), output bias (Kasneci et al., 2023), output fairness (Helberger et al., 2020). Hence, the items have been operationalized using the abovementioned topics and they have been framed as perceived benefits, perceived risks, and trust – that have been proved, by Njiku et al. (2019), to be the most used constructs, both individually and combined, to reflect the attitude of technology adoption in education.

vii. The moderators used are Age and Gender, derived from both Venkatesh et al. (2003) and Woodbury & Gess-Newsome (2002); and some of the school-related experiences highlighted in Woodbury & Gess-Newsome (2002), i.e., number of years of teaching experience; subject(s) taught; type of school; experience in private versus public school.

Moreover, some other decisions have been made:

- Both literature (Hevner et al., 2004) and previous experience (Venkatesh et al., 2003) suggests that the highest loading items for each scale should be used. However, due to the number of constructs, parsimony in the items has been an influent factor (Netemeyer et al., 2003). Thus, each latent variable in the model was operationalized through a set of 3 to 4 items.

- 7-point Likert scales were employed in all survey items, serving as indicators for latent model variables. 7-point scales were chosen over 5-point scales to increase the granularity of the scale and thus its sensitivity as a measurement instrument (Van Thiel, 2014).

- Besides DU and UB, that are based on frequency, and the moderators, that have their own measurement systems, all the scale's endpoints have been labelled with the values "strongly disagree" and "strongly agree". Hence, these scales were presented in such a way that they can be treated at least as interval, or more precisely, as quasi-metrical scales. This allowed for the numeric computations. This scale design is thus in line with the requirements for the Structural Equation Modelling (SEM) technique employed for data modelling (Van Thiel, 2014).

5.2.2.4 Measurement properties: Dimensionality, Reliability and Validity

"A measure's dimensionality is concerned with the homogeneity of items" (Netemeyer et al., 2003, p.9). In this study this is assessed through Cronbach's alpha (Cronbach, 1951). However, Cronbach's alpha simultaneously measures another property: reliability. This "is concerned with that portion of measurement that is due to permanent effects that persists from sample to sample" (Netemeyer et al., 2003, p.10). Considering that this study is not repeated over time, only *internal consistency*, i.e., the interrelatedness among items or set of items, will be assessed. In addition to Cronbach's alpha, Average Variance Extracted (AVE) and Composite Reliability (CR) (Bacon et al., 1995; Raykov, 1997) are also applied. These also measures validity, that it "refers to how well a measure actually measures the construct it is intended to measure" (Netemeyer et al., 2003, p.11).

Finally, multicollinearity is the situation in which there is a strong correlation between two or more predictors (Field, 2017). This could limit the size of the coefficient correlation r and the importance of predictors would be impossible to be estimated. This is measured through Variance Inflation Factor (VIF).

The minimum accepted values of the measures are: 0,7 for Cronbach's alpha (Tavakol & Dennick, 2011); 0,7 for AVE (Urbach and Ahlemann, 2011); 0,5 for CR (Hair et al., 2011). For VIF, instead, the acceptable range is 3,3 to 5 (Kock and Lynn, 2012). Data on the properties is reported in the results section.

5.3 Data analysis procedure

To test the above-mentioned amended UTAUT model, Partial Least Squares Structural Equation Modelling (PLS-SEM) is employed using SmartPLS (Ringle et al., 2015). Effects (path coefficients) are computed using the basic PLS path modelling algorithm in SmartPLS. Following the explanations by Ringle et al. (2015), the basic PLS algorithm is an implementation of the method developed by Lohmöller (2013), Wold (1982) and other contributors. Further, a non-parametric significance test is conducted using a bootstrapping approach. The bootstrapping algorithm implemented in SmartPLS follows the method established by Efron and Tibshirani (1986) and Davison and Hinkley (1997) (Ringle et al., 2015). Ringle et al. (2015) further refer to Hair et al. (2017) for a detailed account on the method.

5.4 Data cleaning

Prior to the PLS-SEM modelling, some data cleaning and pre-processing decisions are made on the raw survey data in preparation for the modelling stage. This is done using Microsoft Excel (Microsoft Corporation, 2024). This process includes:

- Acclaration of the numbers: the survey had a total of 176 responses, 128 of which were complete and 48 of which were partial. This implies 22,92% total responses of the contacted population (768 teachers), 16,66% complete responses of the contacted population, and 6,25% partial responses of the contacted population. Of the responses, 72,72% were complete and 27,27% were partial.

- Data removal: the partial responses have been excluded from the final data. Then, of the complete 128 responses, 3 of them are found to be either duplications (one of them) or with repetitive answers (two of them). Thus, the final responses considered are 125.
- Reverse coding: one of the items, AT2, presented a reverse coding. Thus, its records are flipped in the Likert scale 1-7 used.
- Formulation of percentages: some moderators, the ones concerning the experience in public and private schools, presented absolute data (i.e., total number of years), but to calculate also the percentage of the total experience, two new columns have been added that expressed that concept in a percentage.
- Conversion to binary system: some moderators, namely Gender, SubjectXP, and SchoolXP, are subdivided (SubjectXP in Humanities, Social Sciences, STEM; SchoolXP in Liceo, Tecnico, Professionale) and converted into numerical binary coding so that SmartPLS (Ringle et al., 2015) can read and use them.

A comparison of this study's demographics with the Italian teacher's population can be found in the results section.

5.5 Methodological Limitations

The methodology explained so far does present necessarily two limitations. The first is indeed related to time: the data gathering part of this study is conducted as a snapshot of the situation. Thus, there is no collection of data through numerous, consecutive measurements, that would ensure more precise and reliable results. A second obvious limitation is space: this study uses only a partial sample of the total number of secondary education teachers working in Italy. Thus, to ensure that the results presented in this research are consistent, other surveys should be executed. Moreover, the partial exploratory nature of the study requires corrections and future hypotheses that would amend the proposed and the emerging models.

6 Results

This chapter outlines the findings of the empirical evaluation of this study. Before any analysis, the demographics are showed. Then, to ensure that the choices written in the methodology section are respected, these results are showed according to the order advised by Hair et al. (2019): firstly, the measurement model is assessed, divided into the reflective and formative components. Secondly, the structural model is assessed, divided into correlations, coefficient of determination, path coefficients, and moderations. Finally, all hypotheses are accepted or rejected, and the emerging model is presented.

Study Demographics					Population Demographics				
Gender					Gender				
	M		29	23,2%		M			33,0%
	F		96	76,8%		F			67,0%
Age					Age				-
		Min	Max	Avg			Min	Max	Avg
		25	66	49,952			25	66	50,2
Experience					Experience				
			90	72,0%					
YearsXP					YearsXP				
		Min	Max	Avg			Min	Max	Avg
		1	44	19,392			1	44	
PubXP									
		Min	Max	Avg					
		1	38	17,744					
PriXP									
		Min	Max	Avg					
		0	28	1,816					
Subject									
	Humanities								
			61	48,8%					
	SocSciences								
			32	25,6%					
	STEM								
			35	28,0%					
School type									
	Liceo								
			76	60,8%					
	Tecnico								
			34	27,2%					
	Professionale								
			26	20,8%					

Table 2: demographics

Study demographics show quite similar gender and age distributions to population demographics (OECD, 2023). Total years of experience is also comprehensive, since the retirement age in Italy is 67. Other data of population unfortunately was not found.

6.1 Measurement model

6.1.1 Reflective constructs – proposed model

The first step concerns the loadings of the items: it refers to the degree of explanation of an item's variance by its construct. They appear as follows:

	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB
ITEM1	0.879	0.968	0.819	0.902	0.917	0.777	0.891	0.938	0.887	0.741	0.866
ITEM2	0.139	0.960	0.833	0.907	0.921	0.688	0.895	0.959	0.926	0.877	0.803
ITEM3	0.812	0.953	0.880	0.878	0.598	0.837	0.927	0.942	0.902	0.774	0.789
ITEM4	0.641		0.774			0.880	0.915	0.952	0.692		0.871

Table 3: item loadings – proposed model

The recommended minimum value by Hair et al. (2019) is 0.708, so that the construct can explain at least 0.500 – half – of the item's variance – hence, the indicator's reliability is considered acceptable. The items that don't respect this threshold are AT2, AT4, FC3, PD2, SE4.

The second step also evaluates reliability – specifically internal consistency reliability. It does that by providing Cronbach's alpha and composite reliability value. They appear as follows:

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
AT	0.581	0.861	0.741
BI	0.958	0.958	0.973
DU	0.848	0.856	0.897
EE	0.877	0.881	0.924
FC	0.782	0.908	0.862
PD	0.827	0.924	0.875
PE	0.928	0.930	0.949
PIN	0.962	0.963	0.972
SE	0.876	0.907	0.916
SI	0.715	0.730	0.841
UB	0.854	0.877	0.900

Table 4: internal consistency reliability - proposed model

The recommended thresholds for both measures are 0.6 for exploratory constructs and 0.7 for explanatory. The only construct that does not respect it is AT regarding Cronbach's alpha.

In the third step convergent validity is assessed. This is done via Average Variance Extracted (AVE). It appears as follows:

	Average variance extracted (AVE)		Average variance extracted (AVE)
AT	0.466	PE	0.823
BI	0.922	PIN	0.898
DU	0.685	SE	0.734
EE	0.803	SI	0.639
FC	0.682	UB	0.694
PD	0.638		

Table 5: Average Variance Extracted - proposed model

The minimum threshold for AVE is 0.5, which means that the variable provides an explanation for at least 50% of the indicator's variance. The only construct that does not respect it is AT.

In the fourth step, discriminant validity, that is "the extent to which a construct is empirically distinct from other constructs in the structural model" (Hair et al., 2019, p. 9) is assessed. The measure used is the heterotrait-monotrait (HTMT) ratio. It appears as follows:

HTMT	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB
AT											
BI	0.634										
DU	0.285	0.247									
EE	0.615	0.595	0.140								
FC	0.173	0.267	0.150	0.569							
PD	0.368	0.342	0.181	0.161	0.105						
PE	0.619	0.805	0.328	0.594	0.334	0.385					
PIN	0.470	0.635	0.447	0.693	0.237	0.261	0.538				
SE	0.339	0.575	0.165	0.750	0.444	0.176	0.465	0.664			
SI	0.247	0.288	0.107	0.408	0.657	0.111	0.362	0.101	0.239		
UB	0.564	0.616	0.372	0.536	0.371	0.230	0.569	0.483	0.594	0.227	

Table 6: HTMT - proposed model

Maximum value accepted for HTMT is 0.9. All constructs are below such threshold.

6.1.2 Formative constructs – proposed model

In this study, formative measurement models are evaluated on three elements. The first one concerns item collinearity: as mentioned in the methodology, this is assessed through Variance Inflation Factor (VIF). In the proposed model, data appear as follows:

VIF		SE2	4.285	PE1	2.804	SI1	1.265	FC1	2.059	BI1	6.995
		SE3	3.234	PE2	2.929	SI2	1.777	FC2	2.417	BI2	5.980
AT1	1.303	SE4	1.556	PE3	4.698	SI3	1.562	FC3	1.383	BI3	5.127
AT2	1.004	PD1	2.623	PE4	4.275	PIN1	5.303	DU1	2.630	UB1	2.137
AT3	2.269	PD2	2.380	EE1	2.832	PIN2	7.266	DU2	3.173	UB2	1.949
AT4	1.927	PD3	1.923	EE2	2.982	PIN3	5.324	DU3	2.604	UB3	1.831
SE1	3.069	PD4	1.873	EE3	1.976	PIN4	6.338	DU4	1.680	UB4	2.215

Table 6: VIF - proposed model

As seen in the table above, the two constructs that possess variables that evidently suffer from multicollinearity are PIN and BI. Such results are surprising, due to the long-term commitment that literature has made to these constructs. A more developed analysis on this regard is found in the following chapter. For now, such items and constructs will be treated as if they were not suffering from multicollinearity.

The second and third elements assessed in the formative part are item weights significance and relevance – i.e., the “size”. Significance is determined by the p-value and the t-value of the outer weights obtained in the Bootstrap of the model. In the proposed model, data appear as follows:

	T-value	P-values		T-value	P-values
AT1 <- AT	7.927	0.000	PD1 <- PD	3.651	0.000
AT2 <- AT	1.222	0.222	PD2 <- PD	1.495	0.135
AT3 <- AT	9.454	0.000	PD3 <- PD	5.075	0.000
AT4 <- AT	2.637	0.008	PD4 <- PD	4.458	0.000
DU1 <- DU	4.547	0.000	SE1 <- SE	11.257	0.000
DU2 <- DU	2.731	0.006	SE2 <- SE	17.722	0.000
DU3 <- DU	5.104	0.000	SE3 <- SE	11.737	0.000
DU4 <- DU	3.831	0.000	SE4 <- SE	7.266	0.000
UB1 <- UB	11.547	0.000	SI1 <- SI	2.085	0.037
UB2 <- UB	9.931	0.000	SI2 <- SI	3.183	0.001
UB3 <- UB	7.323	0.000	SI3 <- SI	2.008	0.045
UB4 <- UB	10.683	0.000	EE1 <- EE	21.503	0.000
PIN1 <- PIN	28.326	0.000	EE2 <- EE	19.763	0.000
PIN2 <- PIN	34.645	0.000	EE3 <- EE	16.583	0.000
PIN3 <- PIN	25.810	0.000	BI1 <- BI	43.250	0.000
PIN4 <- PIN	27.402	0.000	BI2 <- BI	35.195	0.000
PE1 <- PE	19.609	0.000	BI3 <- BI	39.652	0.000
PE2 <- PE	17.363	0.000	FC1 <- FC	10.248	0.000
PE3 <- PE	24.118	0.000	FC2 <- FC	11.587	0.000
PE4 <- PE	21.894	0.000	FC3 <- FC	1.547	0.122

Table 7: item weights significance - proposed model

For an item to be significant, p-value must be lower than 0.05 and t-value must be higher than 1.96. The three items that do not respect such thresholds are AT2, PD2, FC3.

The relevance of items, instead, is expressed in a scale comprised between -1 and +1. A weight close to -1 indicates negative, strong size, while a weight close to +1 indicates positive, strong size. A weight close to 0 indicates weak or non-existent relevance. In the proposed model, data appear as follows:

	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB
ITEM1	0.637	0.354	0.326	0.365	0.524	0.268	0.287	0.263	0.301	0.412	0.346
ITEM2	0.104	0.349	0.217	0.346	0.468	0.146	0.288	0.259	0.348	0.472	0.244
ITEM3	0.380	0.338	0.309	0.407	0.148	0.324	0.271	0.278	0.292	0.363	0.253
ITEM4	0.182		0.362			0.478	0.257	0.256	0.212		0.350

Table 8: item weights relevance - proposed model

With the table above, the assessment of the measurement model is concluded. However, the results have shown that, before starting the structural model analysis, some elements must be considered: AT2, AT4, FC3, PD2, SE4 did not pass the reliability test. However, when translating items' scores into construct reliability and validity, only AT presents some issues. Hair et al. (2019) and Hair et al. (2022) suggest dropping an item if it is not significant and its loading is lower than 0.5 – i.e., it is not reliable. The only item that corresponds to such description is AT2. Thus, the model is corrected and run again with AT2 removed from AT.

6.1.3 Reflective constructs – corrected model

The results of the new reflective constructs measurement are:

	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB
ITEM1	0.883	0.968	0.819	0.902	0.917	0.777	0.891	0.938	0.887	0.737	0.865
ITEM2		0.960	0.833	0.907	0.921	0.688	0.895	0.959	0.926	0.878	0.803
ITEM3	0.818	0.953	0.880	0.878	0.598	0.837	0.927	0.942	0.902	0.776	0.789
ITEM4	0.645		0.774			0.880	0.915	0.952	0.692		0.871

Table 9: item loadings – corrected model

In the new loadings, FC3, PD2, SE4, and AT4 do not reach the minimum threshold – as it happened before. However, all of them remain above 0.5.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AT	0.744	0.899	0.829	0.621

BI	0.958	0.958	0.973	0.922
DU	0.848	0.856	0.897	0.685
EE	0.877	0.882	0.924	0.803
FC	0.782	0.908	0.862	0.682
PD	0.827	0.924	0.875	0.638
PE	0.928	0.930	0.949	0.823
PIN	0.962	0.963	0.972	0.898
SE	0.876	0.907	0.916	0.734
SI	0.715	0.731	0.841	0.639
UB	0.854	0.876	0.900	0.694

Table 10: internal consistency reliability and AVE - corrected model

In the new Cronbach's alpha, Composite Reliability and Average Variance Extracted, no construct is below the minimum threshold. Thus, removing AT2 from the model improved the overall results of AT.

	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB
AT											
BI	0.565										
DU	0.255	0.247									
EE	0.502	0.595	0.140								
FC	0.128	0.267	0.150	0.569							
PD	0.342	0.342	0.181	0.161	0.105						
PE	0.575	0.805	0.328	0.594	0.334	0.385					
PIN	0.406	0.635	0.447	0.693	0.237	0.261	0.538				
SE	0.277	0.575	0.165	0.750	0.444	0.176	0.465	0.664			
SI	0.182	0.288	0.107	0.408	0.657	0.111	0.362	0.101	0.239		
UB	0.522	0.616	0.372	0.536	0.371	0.230	0.569	0.483	0.594	0.227	

Table 11: HTMT - corrected model

In the new HTMT ratio, all constructs are below the maximum threshold. Thus, all items and constructs surpassed the reflective constructs analysis.

6.1.4 Formative constructs – corrected model

In the corrected model, VIF appear as follows:

VIF		PE1	2.804	SI1	1.265	FC1	2.059	AT1	1.300	PD1	2.623
		PE2	2.929	SI2	1.777	FC2	2.417	AT3	2.267	PD2	2.380
UB1	2.137	PE3	4.698	SI3	1.562	FC3	1.383	AT4	1.925	PD3	1.923
UB2	1.949	PE4	4.275	PIN1	5.303	SE1	3.069	DU1	2.630	PD4	1.873
UB3	1.831	EE1	2.832	PIN2	7.266	SE2	4.285	DU2	3.173	BI1	6.995
UB4	2.215	EE2	2.982	PIN3	5.324	SE3	3.234	DU3	2.604	BI2	5.980

		EE3	1.976	PIN4	6.338	SE4	1.556	DU4	1.680	BI3	5.127

Table 12: VIF - corrected model

As seen in the table above, PIN and BI still suffer from multicollinearity. Again, such results are surprising, due to the long-term commitment that literature has made to these constructs. A more developed analysis on this regard is found in the following chapter. For now, such items and constructs will be treated as if they were not suffering from multicollinearity.

The weights significance in the corrected model appear as follows:

	T values	P values		T values	P values
AT1 <- AT	7.783	0.000	PE1 <- PE	19.431	0.000
AT3 <- AT	9.734	0.000	PE2 <- PE	17.530	0.000
AT4 <- AT	2.609	0.009	PE3 <- PE	24.270	0.000
BI1 <- BI	43.547	0.000	PE4 <- PE	22.030	0.000
BI2 <- BI	35.395	0.000	PIN1 <- PIN	28.228	0.000
BI3 <- BI	39.902	0.000	PIN2 <- PIN	34.917	0.000
DU1 <- DU	4.550	0.000	PIN3 <- PIN	25.463	0.000
DU2 <- DU	2.733	0.006	PIN4 <- PIN	27.241	0.000
DU3 <- DU	5.108	0.000	SE1 <- SE	11.259	0.000
DU4 <- DU	3.833	0.000	SE2 <- SE	17.724	0.000
EE1 <- EE	21.596	0.000	SE3 <- SE	11.739	0.000
EE2 <- EE	19.663	0.000	SE4 <- SE	7.268	0.000
EE3 <- EE	16.474	0.000	SI1 <- SI	2.058	0.040
FC1 <- FC	10.246	0.000	SI2 <- SI	3.333	0.001
FC2 <- FC	11.586	0.000	SI3 <- SI	2.048	0.041
FC3 <- FC	1.546	0.122	UB1 <- UB	11.568	0.000
PD1 <- PD	3.653	0.000	UB2 <- UB	10.028	0.000
PD2 <- PD	1.496	0.135	UB3 <- UB	7.383	0.000
PD3 <- PD	5.075	0.000	UB4 <- UB	10.697	0.000
PD4 <- PD	4.458	0.000			

Table 13: item weights significance - corrected model

As it can be seen in the table above, FC3 and PD2 still remain non-significant. However, since their loadings are still above 0.5, they are kept in the model.

The weights relevance in the corrected model appear as follows:

	AT	BI	DU	EE	FC	PD	PE	PIN	SE	SI	UB

ITEM1	0.643	0.354	0.326	0.364	0.524	0.268	0.287	0.263	0.301	0.407	0.345
ITEM2		0.350	0.217	0.345	0.468	0.146	0.288	0.259	0.348	0.475	0.245
ITEM3	0.384	0.338	0.309	0.408	0.148	0.324	0.271	0.278	0.292	0.364	0.253
ITEM4	0.183		0.362			0.478	0.257	0.256	0.212		0.350

Table 14: item weights relevance - corrected model

The three items that contribute less to their own construct formation are AT4, FC3, PD2. However, although their relevance is weak, they still can be considered having a positive impact on their own construct formation.

Formative model assessment is concluded. The next subsection will proceed with structural model assessment.

6.2 Structural model

6.2.1 Coefficient correlations

The first step concerns the assessment of the correlations among constructs, *r*, and the significance of each construct, p. In this model *r* appears as follow:

	AT	**BI**	**DU**	**EE**	**FC**	**PD**	**PE**	**PIN**	**SE**	**SI**	**UB**
AT											
BI	0.577										
DU	0.230	0.228									
EE	0.434	0.552	0.121								
FC	0.136	0.271	0.037	0.502							
PD	0.333	0.351	0.126	0.148	-0.062						
PE	0.606	0.761	0.287	0.542	0.331	0.374					
PIN	0.431	0.609	0.401	0.644	0.235	0.241	0.510				
SE	0.265	0.536	0.141	0.673	0.430	0.133	0.435	0.617			
SI	0.154	0.241	-0.035	0.319	0.491	0.038	0.299	0.085	0.186		
UB	0.492	0.573	0.332	0.478	0.358	0.216	0.519	0.450	0.530	0.177	

Table 15: construct correlations

The significance of each construct, instead, corresponds to:

	p-value	
AT	0.013	*
BI	0.000	***
DU	0.376	
EE	0.048	*
FC	0.000	***
PD	0.098	

PE	0.000	***
PIN	0.000	***
SE	0.045	*
SI	0.000	***
UB	0.000	***

Table 16: construct significance (* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$)

As showed in the table above, DU and PD are the constructs that do not respect the threshold of 0.05 of p-value for significance. Thus, both DU and PD are non-significant. Implications are discussed in the following chapter.

6.2.2 Coefficient of determination

The second step involves the coefficient of determination (R^2), i.e., the value that measures the explained variance of a dependent variable. R^2 presents the following scores:

	R-square	R-square adjusted
AT	0.392	0.372
BI	0.820	0.714
EE	0.508	0.500
PE	0.189	0.182
PIN	0.380	0.375
UB	0.767	0.675

Table 17: coefficient of determination

The explanatory power of the predictors of BI and UB is substantial ($R^2 > 0.75$); of EE is moderate ($R^2 > 0.5$); of AT and PIN is weak ($R^2 > 0.25$). PE appear to be not explained.

6.2.3 Path coefficients

Thirdly, path coefficients significance (p-value) and relevance (size) are assessed. Data on significance of direct paths appears as follows:

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	
AT -> BI	0.122	0.114	0.083	1.463	0.144	
AT -> UB	0.218	0.216	0.087	2.499	0.012	*

BI -> UB	0.331	0.322	0.085	3.887	0.000	***
DU -> BI	-0.075	-0.062	0.064	1.165	0.244	
DU -> UB	0.197	0.204	0.073	2.686	0.007	**
EE -> AT	0.100	0.083	0.109	0.917	0.359	
EE -> BI	0.023	0.031	0.099	0.234	0.815	
FC -> BI	-0.010	-0.003	0.073	0.136	0.892	
FC -> EE	0.262	0.263	0.068	3.838	0.000	***
FC -> UB	0.232	0.235	0.082	2.825	0.005	**
PD -> BI	0.049	0.060	0.064	0.766	0.443	
PD -> UB	0.016	0.020	0.080	0.196	0.844	
PE -> AT	0.506	0.513	0.087	5.816	0.000	***
PE -> BI	0.522	0.512	0.093	5.638	0.000	***
PIN -> AT	0.112	0.127	0.100	1.121	0.262	
PIN -> BI	0.293	0.290	0.083	3.553	0.000	***
SE -> EE	0.560	0.563	0.057	9.809	0.000	***
SE -> PE	0.435	0.438	0.072	6.034	0.000	***
SE -> PIN	0.617	0.620	0.055	11.188	0.000	***
SI -> AT	-0.038	-0.031	0.091	0.418	0.676	
SI -> BI	0.034	0.041	0.079	0.438	0.661	

Table 18: path significance (* = p < 0.05; ** = p < 0.01; *** = p < 0.001)

As showed in the table above, AT to BI, DU to BI, EE to AT and BI, FC to BI, PD to BI and UB, PIN to AT and SI to AT and BI are non-significant paths. Data on specific indirect effects is also estimated. For sake of brevity, only the significant paths will be shown here.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	
SE -> PIN -> BI	0.181	0.179	0.052	3.465	0.001	**
PE -> BI -> UB	0.173	0.165	0.053	3.248	0.001	**
PIN -> BI -> UB	0.097	0.093	0.037	2.634	0.008	**

SE -> PE -> AT	0.220	0.224	0.051	4.346	0.000	***
SE -> PE -> BI	0.227	0.225	0.058	3.908	0.000	***
PE -> AT -> UB	0.110	0.112	0.052	2.127	0.033	*
SE -> PIN -> BI -> UB	0.060	0.058	0.023	2.585	0.010	*
SE -> PE -> BI -> UB	0.075	0.072	0.027	2.824	0.005	**

Table 19: indirect path significance (* = p < 0.05; ** = p < 0.01; *** = p < 0.001)

As shown in the table above, BI mediates PE and PIN paths to UB; PE mediates SE to AT and BI; PIN mediates SE to BI; AT mediates PE to UB; SE is mediated by PIN to BI and, subsequently, by BI to UB; SE is mediated by PE to BI and, subsequently, by BI to UB.

	AT	**BI**	**EE**	**PE**	**PIN**	**UB**
AT		0.039				0.086
BI						0.049
DU		0.048				0.194
EE	0.100	-0.286				
FC		0.039	0.262			0.380
PD		0.094				-1.369
PE	0.506	0.262				
PIN	0.112	0.237				
SE			0.560	0.435	0.617	
SI	-0.038	0.278				

Table 20: path size

The minimum value for a path size to be relevant is 0.2, ideally 0.3 (Chin, 1998). As such, the paths from FC to UB, PE to AT, and SE to EE, PE and PIN are ideal. The paths from FC to EE, PE to BI, PIN to BI, SI to BI are relevant.

Thus, combining the path results, considering also the indirect effects, i.e., the possible mediations, the paths that emerge as significant and relevant are:

SE -> PE	0.435
SE -> PIN	0.617
SE -> EE	0.560
SE -> PE -> AT	0.220
PE -> BI	0.262
PE -> AT	0.506
PIN -> BI	0.237
FC -> EE	0.262

FC -> UB	0.380

Table 21: emerging paths

Finally, although numbers show that they are not relevant, AT to UB and BI to UB paths are accepted due to, respectively, i) evident issues with the conceptualization and operationalization of AT, and ii) amount of literature on the topic.

6.2.4 Moderation – Simple Slope Analysis

Having stated that only the paths listed in the table above are the significant and relevant ones, the moderation effects shown in this subsection concerns only them. As such, they are Age and Gender, moderating PE to BI; Age and Experience, moderating FC to UB.

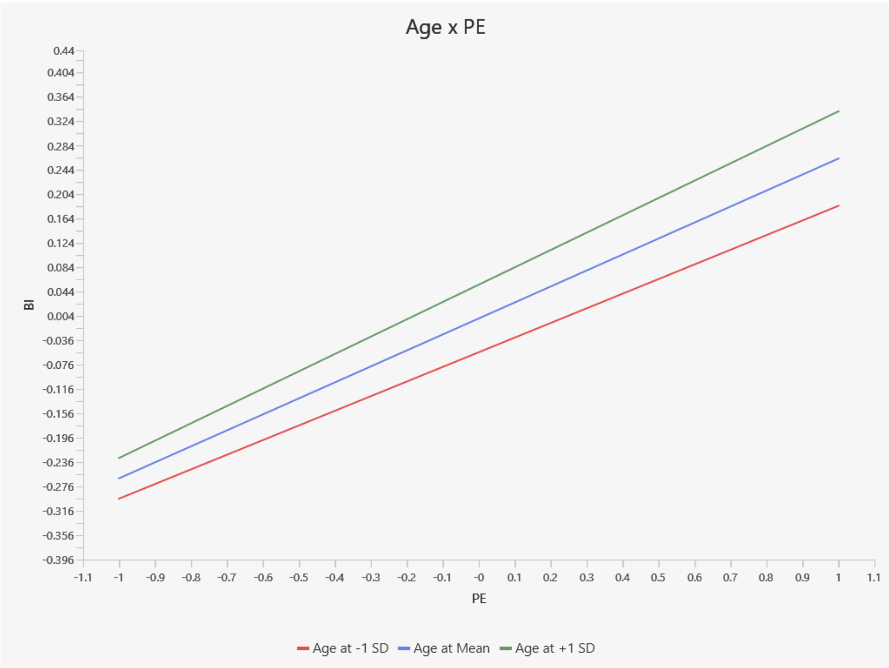

Figure 20: AGE x PE to BI

As the graphic above shows, for all different age groups – younger than the average, average, older than the average of the sample – the relationship between PE and BI remains positive and linear. However, for the same score on PE, the score on BI will be always slightly higher with older individuals. This means that, for an even score of PE, older individuals will always have slightly, higher intention to use AIED. As such, Age does slightly moderate PE influencing BI.

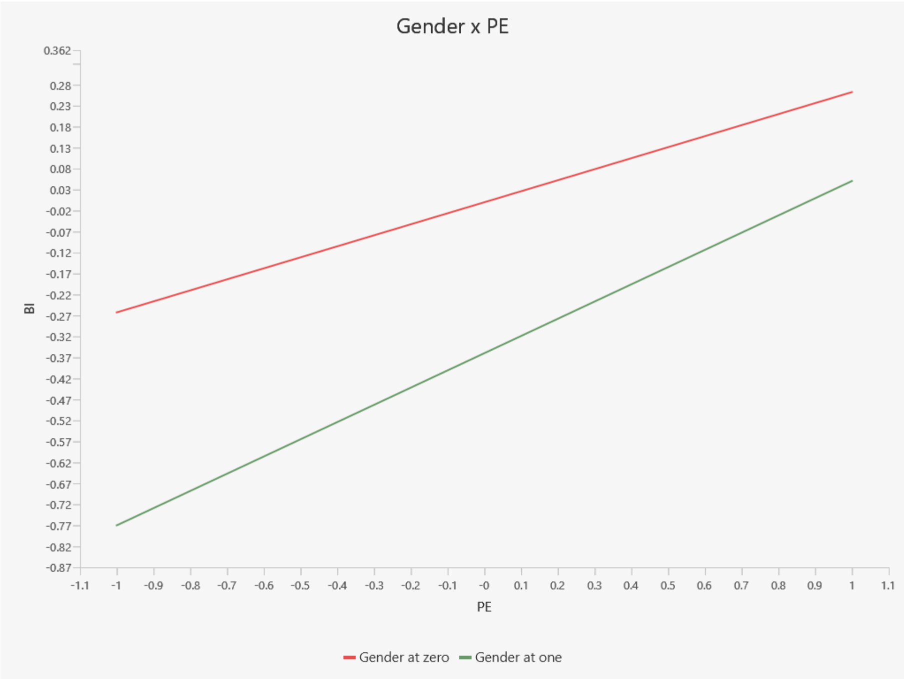

Figure 21: GENDER x PE to BI

As the graphic above shows, for both genders – male at zero and female at one – the relationship between PE and BI remains positive, although it is slightly flatter and significantly above if the gender is male. This means that i) with the same score on PE, a male individual would have a higher score on BI than a female individual; ii) this difference in score in BI at even score in PE shortens as the score on PE increases. As such, Gender does moderate PE influencing BI.

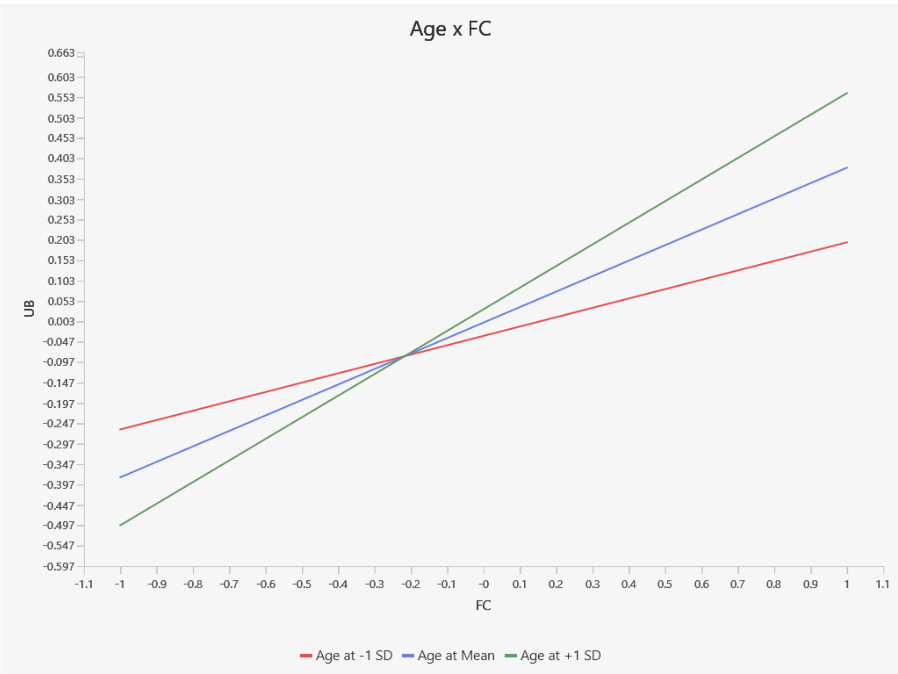

Figure 22: AGE x FC to UB

As the graphic above shows, for all different age groups – younger than the average, average, older than the average of the sample – the relationship between FC and UB remains positive. However, it flattens as age decreases and it converges for all age groups when FC is almost zero (roughly equals to -0.2 SD). This means that i) for an even and bigger than -0.2 SD score on FC, an older individual would score higher on UB; ii) for an even and smaller than -0.2 SD score on FC, an older individual would score lower on UB. As such, Age does moderate FC influencing UB.

Figure 23: EXPERIENCE x FC to UB

As the graphic above shows, the relationship between FC and UB changes significantly with the two levels of experience – one means that the individual has no experience whatsoever in the usage of AIED, while zero means that the individual has at least some experience in the usage of AIED[6]. For the individuals with no experience, the relationship is flat - stable to a negative value of UB (roughly equals to -1.1 SD); meanwhile, for the individuals with experience, the relationship is positive, and its lower score on UB is significantly higher than the no-experience stable score (roughly equals to -0.4 SD). This means that i) if an individual does not have any experience with AIED, whatever its score, and thus opinion, on FC is, it will almost never try to use AIED; ii) if an individual does have experience with AIED, the higher its score on FC is, the higher the probability of AIED adoption. As such, Experience does moderate FC influencing UB.

[6] We understand it could be confusing, since normally researcher would put at zero the negation of a construct and at one the confirmation. However, this happened because the construct of Experience was derived by the mean of the UB of each respondent, that is, one if the answer to all the items of UB was one (i.e., “never”, the minimum score); different to one if at least one answer was more than one. We apologize for the possible confusion.

6.3 Hypotheses acceptance and rejection

Number	Letter	Path	Result
1	A	PE to AT	accepted
	B	PE to BI	accepted
2	A	EE to AT	rejected
	B	EE to BI	rejected
3	A	SI to AT	rejected
	B	SI to BI	rejected
4	A	FC to BI	rejected
	B	FC to UB	accepted
	C	FC to EE	accepted
5	A	AT to BI	rejected
	B	AT to UB	accepted
6		BI to UB	accepted
7	A	PIN to AT	rejected
	B	PIN to BI	accepted
8	A	DU to BI	rejected
	B	DU to UB	rejected
9	A	PD to BI	rejected
	B	PD to UB	rejected
10	A	SE to PE	accepted
	B	SE to EE	accepted
	C	SE to PIN	accepted
11	A	AGE x PE to BI	accepted
	B	AGE x EE to BI	rejected
	C	AGE x SI to BI	rejected
	D	AGE x FC to BI	rejected
	E	AGE x PD to BI	rejected
	F	AGE x FC to UB	accepted
	G	AGE x PD to UB	rejected
12	A	GENDER x PE to BI	accepted
	B	GENDER x EE to BI	rejected
	C	GENDER x SI to BI	rejected
	D	GENDER x PD to BI	rejected
	E	GENDER x PD to UB	rejected
13	A	EXPERIENCE x EE to BI	rejected
	B	EXPERIENCE x SI to BI	rejected

	C	EXPERIENCE x FC to BI	rejected
	D	EXPERIENCE x PD to BI	rejected
	E	EXPERIENCE x FC to UB	accepted
	F	EXPERIENCE x PD to UB	rejected
14	A	YearsXP x PD to BI	rejected
	B	YearsXP x PD to UB	rejected
15	A	PubXP x PD to BI	rejected
	B	PubXP x PD to UB	rejected
	C	PriXP x PD to BI	rejected
	D	PriXP x PD to UB	rejected
	E	Pub/TotXP x PD to BI	rejected
	F	Pub/TotXP x PD to UB	rejected
	G	Pri/TotXP x PD to BI	rejected
	H	Pri/TotXP x PD to UB	rejected
16	A	Humanities x PD to BI	rejected
	B	Humanities x PD to UB	rejected
	C	Social Sciences x PD to BI	rejected
	D	Social Sciences x PD to UB	rejected
	E	STEM x PD to BI	rejected
	F	STEM x PD to UB	rejected
17	A	Liceo x PD to BI	rejected
	B	Liceo x PD to UB	rejected
	C	Tecnico x PD to BI	rejected
	D	Tecnico x PD to UB	rejected
	E	Professionale x PD to BI	rejected
	F	Professionale x PD to UB	rejected

Table 22 hypotheses acceptance and rejection

6.4 The emerging model

Having disposed all the results, a model different from the proposed one emerges. It presents only the constructs and items reliable and valid, and only the significant and relevant path coefficients – with the exceptions of AT to UB and BI to UB, as mentioned before. As such, the graphic looks as follows:

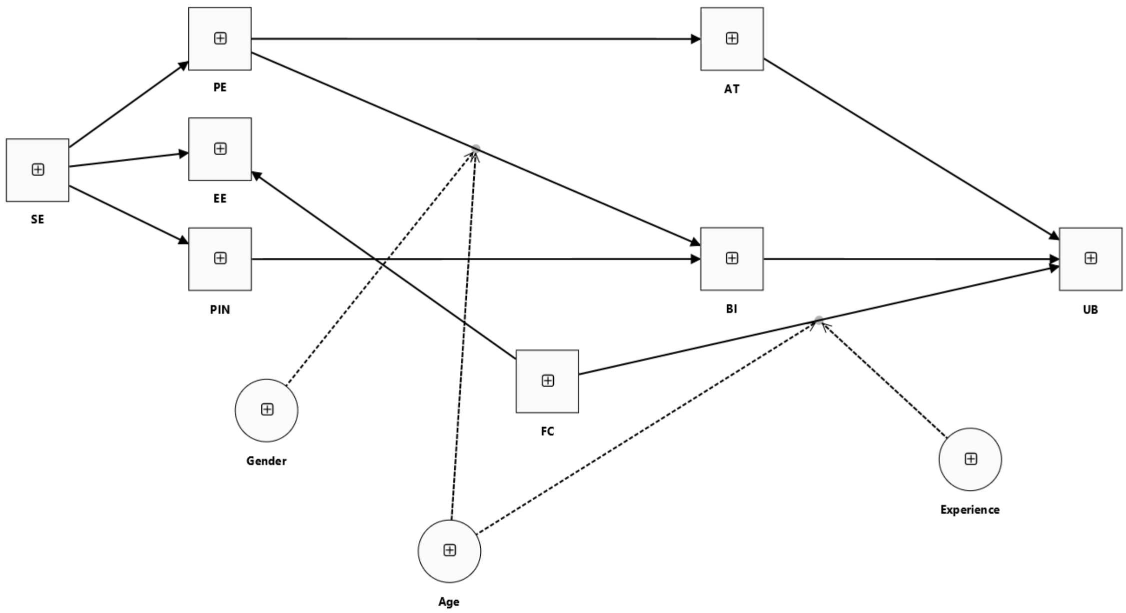

Figure 24: emerging model

7 Discussion

7.1 Model structure and measurement

The first topic bring into discussion is the removal of the item AT2 from the model. The numerical reasons behind this action have been already mentioned in the results section: AT2 was the only item to combine for all three: being lower than the minimum threshold of factor loading for indicator reliability (= 0.500); negatively impacting the internal consistency reliability (Cronbach's alpha = 0.581) and internal validity (AVE = 0.466) of its construct; having a non-significant weight ($t < 1.96$ and $p > 0.05$).

Conceptually, instead, AT is a continuously used construct in IS adoption (Dwivedi et al., 2019), although its conceptualization changes in empirical evaluations, especially in the field of education (Njiku et al., 2019). As such, AT is treated in this research as an exploratory construct and its operationalization is a first-try experiment. Specifically, AT2 was derived by Rudolph et al. (2023) and Hwang et al. (2020), that, in the AI-PS and AIED research fields, noted that the fear of AI replacing humans doing their job could have been a factor in AIED adoption, negatively influencing it.

Dropping such item implies not having an answer to such hypothesis. We suggest that such result has been determined by the probably too-much experimental operationalization of AT: incorporating constructs such as Perceived Risk (for AT2) or Trust into AT was detrimental in the evaluation of such hypotheses. We suggest that, to avoid such results in future research, scientists should not follow the approach used in this research for the operationalization of AT. Rather, they could use either a more traditional approach or develop a more comprehensive construct – i.e., it should have more items to balance the differences among them.

The second topic of the measurement model concerns the outer VIF – that is, assessing multicollinearity within a construct. As showed in the results section, all items from PIN (PIN1, PIN2, PIN3, PIN4) and BI (BI1, BI2, BI3) show a VIF > 5, which is the threshold indicated in literature from which multicollinearity exists (Hair et al., 2019). However, such fundings do not find any support in the literature: firstly, BI is the most used dependent variable in IS adoption research field – and dropping it would completely invalidate the model (and an entire research field!). Secondly, in this study both PIN and BI have been operationalized in their most used way in literature (Agarwal & Prasad, 1998, and Venkatesh et al., 2003, respectively). Thus, these numerical findings are rejected by theory and practice, and the cause of this is attributed to the small sample size – such statement is the best hypothesis in a context in which no hypotheses can be made.

7.2 Significance

The constructs that were stated to be non-significant are DU and PD. Their numerical results (both have $p > 0.05$) imply, probably, that the main cause was their operationalization: DU, for the knowledge of who is writing, has never been used in IS adoption – at least not in the way it was meant to be in this study. In fact, it was proposed because the qualitative literature on AI-PS suggested so (van Noordt & Misuraca, 2022; Agarwal, 2018), and thus, the way such construct should influence intention or use in a quantitative analysis can only be experimented. A possibility suggested by the positive results on Experience as a mediator is to include Digital Use/Experience as a competing mediator and not a predictor.

PD, instead, was introduced in this model to merge two research fields – IS adoption and CCM (Conceptual Change Models). This attempt was indeed risky and in fact this negative result is emblematic. A suggestion for future research, however, is to try new way of including this construct into IS acceptance research. The reason behind this statement relies on the fact that the original Pedagogical Discontentment construct (Southerland et al., 2012) presented 22 items, but for parsimony it was reduced to 4 into this research. There must be, evidently, a numerical compromise that could lead to positive results. Moreover, a significant PD would imply the introduction of all the moderators from CCM research field, that are related to school environment – and had to be dropped due to PD inconsistency.

Concerning path significance, instead, more results need to be discussed: the negative significance of EE to AT, EE to BI, SI to AT, SI to BI, and AT to BI (and the absence of relevance of AT to UB) must be caused by the sample size. The amount of literature on these paths is simply too big to be questioned by one study. A marginal note, however, must be made on EE: Venkatesh et al. (2003) warned about the fact that EE and SE could not coexist in the same model and co-predict BI. Thus, in this study we used a different operationalization of SE (Ng et al., 2021) and we put it as an external variable. Can the positive findings on SE and the negative ones on EE be interpreted as an incompatibility of the two constructs? Literature denies such hypothesis (Dwivedi et al., 2011).

PIN to AT and FC to BI, instead, can be accepted as non-significant paths: the latter was proposed by Dwivedi et al. (2019). However, that study didn't empirically evaluate such statement, based on a reconceptualization of the UTAUT model – that is, a new analysis on old literature. The former, instead, was proposed although the literature did not totally confirm nor denied such hypothesis (Dahri et al., 2024).

7.3 Implications and recommendations

The implications for theory focus on two constructs: firstly, in AIED SE can be conceptualized as the opinion of the degree of possession of the competences required to assess IS/AI literacy (Ng et al., 2021). The positive results of SE open to this direction. Secondly, FC is a predictor of both EE and UB and not of AT and BI: FC to UB is well-established in literature; FC to AT is denied in non-mandatory settings; FC to BI is rejected since, probably, “objective” organizational and infrastructural support does not influence intention, rather direct use. Thus, it does not move individuals into trying IS adoption, but it is a prerequisite to actual adoption; FC to EE is supported by this study: good organizational and technical support make IS/AI adoption easier for individuals.

The recommendations for theory are to find better ways of conceptualizing AT, DU, PD: these constructs have been experimented in this study but evidently the operationalization and/or conceptualization of such concepts did not manage to capture significant relationships. Moreover, moderations on PIN to BI, from FC to EE, and from all the constructs predicting AT to AT have not been hypothesized. Future research should focus on these points.

The implications and recommendations for practice are to pay attention to the self-efficacy of the individuals; to expected performance of AI and personal innovativeness as predictors of intention; to positive attitude, positive intention, positive conditions as separated predictors of use. Moreover, pay attention to the moderators: female users need a very high score on PE so that it could positively influence intention – and, as shown in the demographics, they are the 76,8% of the sample; older users need a very high score on FC (= need a very good support) to use AIED – and the average age of the sample is 50 years; finally, without experience on AIED, users will not try it themselves, whatever support is given them. This latter statement seems a paradox, but it implies that users need to be guided through practical use before giving it the right training and infrastructure that could enhance its use. This means that a multi-phased training should be prepared: first, mandatory, temporary, practical experiments that would give the users enough experience, and second, actual training lessons, in which theory and practice experiments are combined.

8 Conclusion

Concluding, this study investigated the factors influencing Artificial Intelligence in Education (AIED) adoption. It did it proposing a new model based on the integration of technology adoption constructs and models with conceptual change constructs and models. Specifically, the proposed model was based on the reconceptualization of UTAUT as developed by Dwivedi et al. (2019) and it integrated the construct of Pedagogical Discontentment as developed by Southerland et al. (2011) – and its school-related contextual moderators as developed by Woodbury and Gess-Newsome (2002).

Such model was empirically evaluated through a survey on Italian secondary school teachers. The results suggest that PE, PIN and AT are the only constructs directly influencing BI, while AT, BI, and FC directly influence UB. Meanwhile, FC and SE operate as external variables influencing EE, and SE does it as well for PE and PIN. The conceptualization and operationalization of AT, DU, PD evidently did not meet the expectations and require new research on the topic. Age and Gender significantly moderate PE influence on BI, and Age and Experience significantly moderate FC influence on UB.

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Appendix

A Survey Questionnaire

ITEM	SENTENCE	SOURCE	SCALE
SE1	I have the necessary knowledge to understand AI applications in my job	Derived from: Ng et al, 2021	7-point Likert
SE2	I have the necessary skills to correctly use AI in my job	Derived from: Ng et al, 2021	7-point Likert
SE3	I am capable of analysing and evaluating AI decisions in my job	Derived from: Ng et al, 2021	7-point Likert
SE4	I am aware of the ethical issues of AI usage in my job	Derived from: Ng et al, 2021	7-point Likert
PE1	I find AI useful for teaching	Adapted from: Venkatesh et al, 2003	7-point Likert
PE2	Using AI helps me accomplish things more quickly	Adapted from: Venkatesh et al, 2003	7-point Likert
PE3	Using AI increases the personalisation of my teaching	Adapted from: Venkatesh et al, 2003	7-point Likert
PE4	Using AI increases the quality of my teaching	Adapted from: Venkatesh et al, 2003	7-point Likert
EE1	I find AI easily understandable	Adapted from: Venkatesh et al, 2003	7-point Likert
EE2	I find AI easy to use	Adapted from: Venkatesh et al, 2003	7-point Likert
EE3	It is easy for me to become skillful at using AI	Adapted from: Venkatesh et al, 2003	7-point Likert
SI1	My colleagues think that I should use AI for teaching	Adapted from: Venkatesh et al, 2003	7-point Likert

SI2	My school leader think that I should use AI for teaching	Adapted from: Venkatesh et al, 2003	7-point Likert
SI3	Educational policy makers sponsor AI for teaching	Adapted from: Venkatesh et al, 2003	7-point Likert
FC1	I have been sufficiently trained to use AI in my job	Adapted from: Venkatesh et al, 2003	7-point Likert
FC2	The necessary infrastructure to use AI in my job has been provided to me	Adapted from: Venkatesh et al, 2003	7-point Likert
FC3	Someone would be available for assistance if I had difficulties using AI	Adapted from: Venkatesh et al, 2003	7-point Likert
PIN1	I like experimenting with new digital technologies	Adapted from: Agarwal & Prasad, 1998	7-point Likert
PIN2	If I heard about a new digital technology, I would look for ways to experiment with it	Adapted from: Agarwal & Prasad, 1998	7-point Likert
PIN3	Among my family/friends, I am usually the first to try out new digital technologies	Adapted from: Agarwal & Prasad, 1998	7-point Likert
PIN4	In general, I do not hesitate to try out new digital technologies	Adapted from: Agarwal & Prasad, 1998	7-point Likert
PD1	I am not satisfied with the current level of my students' engagement	Derived from: Kasneci et al, 2023; Fives et al, 2015. Structure adapted from: Vila & Kuster, 2011	7-point Likert
PD2	I am not satisfied with the learning outcomes of all the students	Derived from: Southerland et al, 2011; Kasneci et al, 2023. Structure adapted from: Vila & Kuster, 2011	7-point Likert
PD3	I am not satisfied with both depth and breadth of subject's content I teach	Derived from: Southerland et al, 2011; Chen et al, 2020.	7-point Likert

		Structure adapted from: Vila & Kuster, 2011	
PD4	I am not satisfied with my current evaluation practice	Derived from: Southerland et al, 2011; Zawacki-Richter et al, 2019. Structure adapted from: Vila & Kuster, 2011	7-point Likert
DU1	Frequency of use of digital technologies when preparing a lecture	Adapted from: Venkatesh et al, 2012	7-point Likert
DU2	Frequency of use of digital technologies when delivering a lecture	Adapted from: Venkatesh et al, 2012	7-point Likert
DU3	Frequency of use of digital technologies when assigning homeworks	Adapted from: Venkatesh et al, 2012	7-point Likert
DU4	Frequency of use of digital technologies when correcting homeworks/tests	Adapted from: Venkatesh et al, 2012	7-point Likert
AT1	Using AI does foster my independence as a teacher	Derived from: Nazaretski et al, 2022	7-point Likert
AT2	I am afraid of being replaced by AI in my job	Derived from: Rudolph et al, 2023; Hwang et al, 2020	7-point Likert (Reverse Coding)
AT3	I trust AI decisions despite their potential biases	Derived from: Kasneci et al, 2023;	7-point Likert
AT4	I find AI decisions fairer than humans' ones	Derived from: Helberger et al, 2020	7-point Likert
BI1	I intend to use AI in my job in the next year	Adapted from: Venkatesh et al, 2003	7-point Likert
BI2	I will try to use AI in my job in the next year	Adapted from: Venkatesh et al, 2003	7-point Likert

BI3	I am planning to use AI in my job in the next year	Adapted from: Venkatesh et al, 2003	7-point Likert
UB1	Frequency of use of AI that produces, corrects, edits and/or analyses natural language	Adapted from: Venkatesh et al, 2012	7-point Likert
UB2	Frequency of use of AI that produces, corrects, edits and/or analyses coded language	Adapted from: Venkatesh et al, 2012	7-point Likert
UB3	Frequency of use of AI that produces, corrects, edits and/or analyses all types of visual formats (pictures, images, paintings…)	Adapted from: Venkatesh et al, 2012	7-point Likert
UB4	Frequency of use of AI that automatises or fastens researches, calculations, or the production, revision or edit of documents	Adapted from: Venkatesh et al, 2012	7-point Likert
Age	Age	Adapted from: Venkatesh et al, 2003; Woodbury & Gess-Newsome, 2002	Number
Gender	Gender	Adapted from: Venkatesh et al, 2003; Woodbury & Gess-Newsome, 2002	A/B choice
YearsXP	For how many years have you been teaching (this one included)?	Adapted from: Woodbury & Gess-Newsome, 2002	Number
SubjectXP	What is/are the subject(s) that you teach?	Adapted from: Woodbury & Gess-Newsome, 2002	Choice on list
SchoolXP	In what type of school are you teaching?	Adapted from: Woodbury & Gess-Newsome, 2002	Choice on list
PubXP	For how many years have you worked in a public school?	Adapted from: Woodbury & Gess-Newsome, 2002	Number

PriXP	For how many years have you worked in a private school?	Adapted from: Woodbury & Gess-Newsome, 2002	Number

B Survey Questionnaire in Italian

ITEM	**SENTENCE**
SE1	Possiedo la conoscenza necessaria per comprendere l'utilizzo dell'IA nel mio lavoro
SE2	Possiedo le competenze necessarie per usare correttamente l'IA nel mio lavoro
SE3	Sono capace di analizzare e valutare le decisioni dell'IA nel mio lavoro
SE4	Sono a conoscenza dei problemi etici dell'uso dell'IA nel mio lavoro
PE1	Trovo che l'IA sia utile per l'insegnamento
PE2	Usare l'IA velocizza la risoluzione dei miei impegni didattici
PE3	Usare l'IA aumenta la personalizzazione del mio insegnamento
PE4	Usare l'IA aumenta la qualità del mio insegnamento
EE1	Trovo che le IA siano facilmente capibili
EE2	Trovo che l'IA sia facile da usare
EE3	Ritengo sia facile per me diventare abile nell'utilizzare l'IA
SI1	I miei colleghi ritengono che dovrei utilizzare l'IA per insegnare
SI2	Il mio dirigente ritiene che dovrei utilizzare l'IA per insegnare
SI3	I politici e funzionari del Ministero promuovono l'utilizzo dell'IA nella didattica
FC1	Sono stato sufficientemente formato per usare l'IA nel mio lavoro
FC2	Mi è stata fornita l'infrastruttura necessaria per usare l'IA nel mio lavoro
FC3	Se avessi difficoltà nell'utilizzare l'IA nel mio lavoro ci sarebbe una figura predisposta ad aiutarmi

PIN1	Mi piace sperimentare con le nuove tecnologie digitali
PIN2	Se vengo a conoscenza di una nuova tecnologia digitale cerco un modo per sperimentarla
PIN3	Tra le mie conoscenze sono spesso il/la primo/a a provare nuove tecnologie digitali
PIN4	In generale, non esito a provare nuove tecnologie digitali
PD1	Non sono soddisfatto dell'attuale livello di coinvolgimento dei miei studenti
PD2	Non sono soddisfatto dell'attuale livello di apprendimento dei miei studenti
PD3	Non sono soddisfatto dell'ampiezza e della profondità dei contenuti che insegno
PD4	Non sono soddisfatto del mio attuale metodo di valutazione
DU1	Frequenza di utilizzo delle tecnologie digitali nella preparazione di una lezione
DU2	Frequenza di utilizzo delle tecnologie digitali nello svolgimento della lezione
DU3	Frequenza di utilizzo delle tecnologie digitali nel dare compiti a casa
DU4	Frequenza di utilizzo delle tecnologie digitali nel correggere compiti a casa o verifiche
AT1	Usare l'IA favorisce la mia indipendenza come docente
AT2	Ho paura di essere sostituito dall'IA nel mio lavoro
AT3	Mi fido delle decisioni dell'IA nonostante i possibili bias
AT4	Trovo che le scelte delle IA siano più giuste di quelle umane
BI1	Intendo utilizzare l'IA nel mio lavoro il prossimo anno
BI2	Proverò a utilizzare l'IA nel mio lavoro il prossimo anno
BI3	Sto pianificando di utilizzare l'IA nel mio lavoro il prossimo anno
UB1	Frequenza di utilizzo di intelligenze artificiali che producono, correggono, modificano e/o analizzano testi in linguaggi naturali (italiano, inglese, etc)
UB2	Frequenza di utilizzo di intelligenze artificiali che producono, correggono, modificano e/o analizzano stringhe di codice

UB3	Frequenza di utilizzo di intelligenze artificiali che producono, correggono, modificano e/o analizzano formati visivi (fotografie, immagini, opere d'arte, etc)
UB4	Frequenza di utilizzo di intelligenze artificiali che automatizzano o velocizzano ricerche, calcoli, compilazioni di documenti
Age	Età compiuta o da compiersi nel 2024
Gender	Sesso
YearsXP	Compreso l'anno corrente, da quanti anni insegna?
SubjectXP	Qual è la sua classe di concorso?
SchoolXP	In quale tipo di istituto insegna?
PubXP	Compreso l'anno corrente, per quanti anni lei ha insegnato in un istituto pubblico?
PriXP	Compreso l'anno corrente, per quanti anni lei ha insegnato in un istituto privato?