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# Skills substitution and Trust:
# A new conception of attitude towards AI in a-HRM

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## Abstract

Attitude towards new technologies depends on different factors. In case of AI (artificial intelligence), workers may perceive their own skills as easily substitutable and look at their job as likely to be replaced. This perception may have negative impact on their acceptance towards implementation of intelligent machines and automation, if there wouldn’t be a well based trust on the improvements brought by these technologies. Unfolding from such considerations, we have collected data from a diversified sample of 183 workers and requested a bootstrapped estimate from 5,000 samples. As a result, we propose a mediated process between skills substitution and perceived overall job replacement, moderated by trust, which leads to attitude towards AI in *a-HRM* (automated human resources management). Surprisingly for high substitution perceptions, workers manifested more positive attitude towards AI. This provided big room of discussion and great enrichments in current literature; plus considerable practical implication in understanding workers behaviors face automation investments in companies.

**Keywords:** AI; trust; skills replaceability; job replacement**;** a-HRM.

# Resumo

A atitude em relação às novas tecnologias depende de diferentes fatores. No caso da IA (inteligência artificial), os trabalhadores podem perceber as próprias competências como facilmente substituíveis e perceber a instabilidade do seu trabalho. Essa perceção pode ter um impacto negativo na aceitação da implementação de máquinas inteligentes e de investimentos em automação, se não houvesse uma confiança bem fundamentada nas melhorias trazidas por essas tecnologias. Começando de tais considerações, coletamos dados de uma amostra diversificada de 183 trabalhadores e solicitamos uma *bootstrapped estimate* de 5.000 amostras. Como resultado, propomos um modelo mediado entre a substituição de competências e a perceção geral da substituição do trabalho, moderada pela confiança, o que leva a atitude face as IA em *a-HRM* (automated human resources management). Surpreendentemente, para perceções de alta substituição, os trabalhadores manifestaram uma atitude mais positiva em relação as IA. Isso proporcionou grande espaço de discussão e grandes enriquecimentos na literatura atual, mais implicações práticas fundamentais na compreensão dos comportamentos dos trabalhadores em frente aos investimentos em automação nas empresas.



**Palavras-chave:** AI; confiança; substituição de competências; substituição de emprego; a-HRM.

*"Our comforting conviction that the world makes sense rests on a secure foundation: our almost unlimited ability to ignore our ignorance."*

D. Kahneman (2011)

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## Introduction

The exponential technological advance is triggering dynamics that take on different connotations and facets. We hear about automation of production processes following the digitization and development of Artificial Intelligence (AI): we move with a propulsive drive towards the fourth industrial revolution. Although this has been widely discussed, there is a big silence about the social impact these changes have on work and specifically in the HR sector. Considering the historical background it would be surprising if these shifts have no substantial impact on the labor market. More than ever, the increasing complexity and completeness of the machines casts doubts upon the adequacy of human work facing these changes. Based on this assumption, the main objective of this research is to establish to what extent the HRM skills are perceived to be further substituted by machines and how this perception is linked with workers attitude towards AI. In this way, we believe a more appropriate approach or understanding of e-HRM (Electronic Human Resources Management) is called for.

This work unfolds from a central question: in the future, how much will the main human skills be replaced through digitization and automation? Which is the most socially and economically sustainable way to set up and manage an automation investment in HRM function? To answer these critical questions, we need to clarify in detail the most controversial aspects of the phenomenon under analysis. In doing so, we will be able to describe and understand the state of the art and enrich it with further considerations, which we expect to lead to new insights about the issue of skill automation in e-HRM practices.

The fulcrum from which we will start is the awareness that workers have of this phenomenon of automation & AI and the degree of confidence/fear they express about it.

Crossing the results obtained through a quantitative research method with a statistical factorial analysis, we set ourselves the objective to construct a predictive and explanatory model of skills enhancement and replacement by automation technology.

To contextualize and support this research, we will define the limits and opportunities offered by the automation processes and establish its degree of social sustainability. We will question the possible effects of automation on the unemployment rate and on capital trends (Ford, 2015; Piketty, 2017) in order to outline an economic and political background to frame a research model effectively. In this way, we intend to evaluate the real possibility, analyzing costs and opportunities of human work replaceability by artificial intelligence. Furthermore, we intend to analyze the limits of human work: when it becomes obsolete and fallacious, when it no longer represents a profitable source of investment so that, as already happens in various sectors, companies direct their investments towards automation.

Nowadays the discoveries in the field of AI are revolutionizing how one conceives the uniqueness of human work, paving the way for a broader vision of the concept of substitutability (Vermeulen, Kesselhut, Pyka, & Saviotti, 2018). The existing models conceived so far focused on the substitutability of production processes, but by now, this vision seems to be outdated, because the horizons that AI technologies propose reach the emulation or creation of complete cognitive processes, such as dialogue or the definition of objectives and strategies (Brynjolfsson & McAfee, 2014). For this reason, the model that we want to elaborate goes beyond the concept of production process substitutability and embraces social, cognitive, psychological and interactional aspects, as well as functional ones, that compose the basic skills of daily work in HR (Meriac, Hoffman, & Woehr, 2014). Moreover, it differs from previous models of technology acceptance (TAM) (Davis, 1989) as it does not focus on acceptance but rather on the perception that workers have about automation, a real perception based on daily work experience.

We contend that this may add to extant knowledge and theory as well as being of practical relevance in elaborating HR policies targeting human skills development and deployment. Findings may also open ways to support HR strategy for investments in automation and how to reconcile these with the effects produced by the presence of learning machines in organizations, aiming to further social and economic balance.

# 1. Machines and Humans: coming to a turning point

## 1.1. Fourth Industrial revolution and Automation

If we approach human evolution from a technological development perspective, it is easy to observe a linear narrative in which the machines' contribution in improving our lifestyle has grown exponentially. Moments of uncertainty have never characterized significant regressions and we have never doubted the horizon towards which we were moving.

Schwab (2016) reports the beginning of this story at the advent of agriculture, around 10,000 years ago. With the improvement of food production, human moved from a nomadic lifestyle to a sedentary one, this will shortly lead to the birth of the first cities.

New needs have subsequently triggered different ways of conceiving work, especially to replace it. In the second half of the 18$^{th}$ century the first industrial revolution made it possible to replace muscle energy with mechanical energy. A process favored by the construction of railways for moving goods and by the invention of the steam engine. The second industrial revolution, which starts between the end of the 19$^{th}$ century and the beginning of the 20$^{th}$, subsequently made mass production possible thanks to the implementation of the assembly line and the advent of electricity.

Thorough history, technological changes have always involved social mutation: we should not forget that the first and second industrial revolution were triggered by a capitalist spirit born from the Calvinist Protestant Ethic (Weber, 2001). Hence, the *forma mentis* that led human societies to improve the means at their disposal, to increase its efficiency and recapitalize the fruits of their profits. Technological and social revolutions go hand in hand, they are complicit and the changes of one converge on the path of the other.

In 1960 then, people testified the dawn of the third industrial revolution, which was catalyzed by the birth of semiconductors, the improvement of computers and the rise of internet connectivity.

Today, we hear more and more about the fourth industrial revolution, even if we cannot yet establish with certainty the point we are. Contemporary societies are living for sure the *Second Machine Age* (Brynjolfsson & McAfee, 2014), where computers and digitalization are making to mental power what steam has done to physical force. The new technologies are allowing us to break our limits, leading us to the threshold of a new Era whose changes are still to be defined.

Intelligence is the key factor that has allowed man to dominate other species. Without a continuous development of our intelligence none of the aforementioned revolutions would have taken place. At the gates of the fourth industrial revolution, human societies seem to be relying on machines to increase this great power. This defines the uniqueness of this process, which will probably have economic and social consequences whose scope we do not yet realize.

Before going further, we must point out that these revolutions did not have the same relevance all over the globe. The various countries have lived them in different forms and times. Schwab (2016) states that the second industrial revolution has not yet fully developed in 17% of the world, the third still leaves 4 billion people on the sidelines: the inhabitants of the less developed countries that still do not have access to internet.

Despite this, the western world proceeds unabated and bigger changes are continuously produced in several sectors. Also, according to Schwab (2016) we can identify three large megatrends characterizing the fourth revolution: 1. Physical, 2. Digital, and 3. Biological.

It is not in the interest of this treatment to specify these in detail or to analyze their possible and real applications. It is important for us is to understand what is changing and what to expect from these mutations, highlighting our relationship with the new technologies, especially in the workplace.

Analyzing these dynamics in terms of temporality, we certainly notice an exponential acceleration in the way new technologies penetrate our lives.

Alvin Toffler (1980), considered one of the most famous futurologists in the world, scans industrial revolutions by technological waves. Starting from the agrarian revolution, every wave begins with a technological innovation, reaches its peak and then declines, to make room for new technologies. Each of these originates radical changes in lifestyle and production methods. Toffler counted the space between each wave (from agrarian revolution to computer era) and he noticed a progression where the time span covered by a technological wave is halved by 1/10 years (3,000 yrs. → 300 yrs. → 30 yrs. → 3 yrs.). Following this logic, next waves will last for a few months or even days.

Obviously, taking into consideration biological limits this is hardly possible. However starting from the *Information Age* (when internet showed up), we observe the reproduction of minor waves that reflect small, but always important, advances in the field of technological innovation. For example: technology is considered to have penetrated society after being used by at least 50 million people (Rosen, 2010). According to Gazzaley and Rosen (2016), this model have only made sense for a certain period. If we look back, radio took thirty-eight years to reach the goal of 50 million users. Later telephone took twenty years, television thirteen.

Mobile phones have reached the benchmark in 12 years, then Internet has changed the whole dynamic. Internet penetrated developed societies in just four years, after this, the world was flooded with new applications that reached 50 million users in a much shorter period. YouTube took only a year, Angry Birds (the smartphone game) just 35 days. These numbers clarify how the narrative of technological innovation, from a temporal point of view, has more the appearance of an exponential curve. We must therefore re-discuss the ability of society to absorb these changes and assess the possibility of a breaking point.

So far, we have observed a linear and progressive history, with no relevant turning points. The question pertaining artificial intelligence is: will this time be the same again?

With the advent of artificial intelligence, machines are expected to replace what up to here has made us unique as a species and has given us evolutionary advantage: our brain. Therefore, it is normal to ask ourselves what our relationship with future technologies will be, how and to what extent our lives will be impacted.

## 1.2. Impact on Labor Market

Change in production methods may lead to changes in social texture. Today we are in a phase of transition, the post-modern phase, better defined by Bauman (2011) as *Liquid Modernity*. A place where the only constant is change and the only certainty is uncertainty. An indefinite stage, or rather, a non-stage. According to the Polish sociologist this characterization of modernity produces considerable effects on our individuality and emancipation, on our conception and interaction with time and space, on work and on our community composition.

The most relevant characterization for our study is undoubtedly the one related to work. During the 21st century work became extra territorial and incorporeal, following the logic and the rules of free enterprise: it has been dislocated to cheaper labor places. Moreover, having assumed such characteristics, it becomes temporary and flexible, work can now adapt itself to the new changing needs and move according to the volubility of the demand.

Observing these dynamics from a sociological point of view, we note that the whole economic paradigm has recently undergone a radical change. According to Bauman (2011) new technologies have created more products, more connection and therefore more short-term wishes. Relentless consumption, based on desire and its immediate satisfaction, feeds domestic demand. Capital has freed itself from the shackles of the state and politics, becoming light, mobile and dynamic as well. According to Thomas Piketty (2014) that analyzes economic data from the 18th century until the 21st, we see a progressive increase in private capital compared to public one and an incisive increase in the polarization of wealth. The research of the French economist suggests us that the dynamic process of a market economy and private property, if left to itself, feeds important factors of convergence, but also equally worrying factors of divergence of capital.

The main destabilizing factor is linked to the circumstances that led the private return rate on capital $r$ to be bigger for a longer period than the growth rate of revenues and production $g$, thus generating inequality: $r > g$. As a parallel case, digitization and automation mean that companies are not likely to incur a fall in returns to scale, since they will be able to produce with marginal costs tending to zero. Less costs and more production mean more recapitalization, especially in the private sector.

Schwab (2016), offers us a clear example comparing Detroit 1990 with Silicon Valley 2014. In 1990 the three largest companies in Detroit had a total capitalization of $ 36 billion, revenue of $ 250 billion and 1.2 million employees. In 2014, the three largest Silicon Valley companies have a significantly larger total capitalization ($ 1.09 trillion), generating roughly the same revenue ($ 247 billion), but with 10 times less workers (137,000).

The effects of the divergent factors analyzed by Piketty are clear here. Furthermore, we may testify an increase of this tendency, since the labor market has not yet concretely suffered the imminent effects of the fourth industrial revolution.

The acceleration of information technology will probably have a huge impact on future economy and on the labor market, but this impact will be dependent on other driving forces, such as financialization and globalization. So far, these two forces have had the role of bringing problems and benefits on a global scale. It is not difficult to imagine how they can eventually expand the effects deriving from the general automation of workforce.

According to Martin Ford (2015), the line between technology and globalization will be blurrier, as even high-skill jobs will become more vulnerable to electronic offshoring. The low-skilled jobs, on the other hand, those more easily to be replaced by machines, will undergo an inverse trend: if until now they have been outsourced where workforce is cheaper, in future for large companies will be more convenient to bring back home these jobs (*reshoring*) and automate them (Wisskirchen, 2017).

But there are those who look at the phenomenon of automation with greater caution. These more confident scholars approach the problem first from a historical perspective.

David H. Autor (2015) states that in the past two centuries automation and technological advances have not made human work obsolete: the *employment-to-population* ratio has grown during the twentieth century. Substantially, those who state the contrary incur the same mistake committed in the 19th century by the Luddites: a group of English textile artisans who opposed the automation of textile production and that destroyed machines. Obviously, the feared scenario would never have happened and production, demand for goods and work have undergone constant and sustained growth.

Automation, leading to an increase in output, brings greater demand and consequently a greater demand for work. Autor (2015) states that labor market has been victim of increasing polarization, which has been particularly evident in recent years, but he doubts that this will continue in the future. Automation cannot reduce the aggregate demand for work, because work cannot be wholly substituted, but only specific tasks.

We can distinguish five types of tasks: analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks, and manual non-routine tasks. Computers can only replace routine cognitive tasks and routine manual tasks, for the remaining cases they can only be complementary to human work (Dengler & Matthes, 2017).

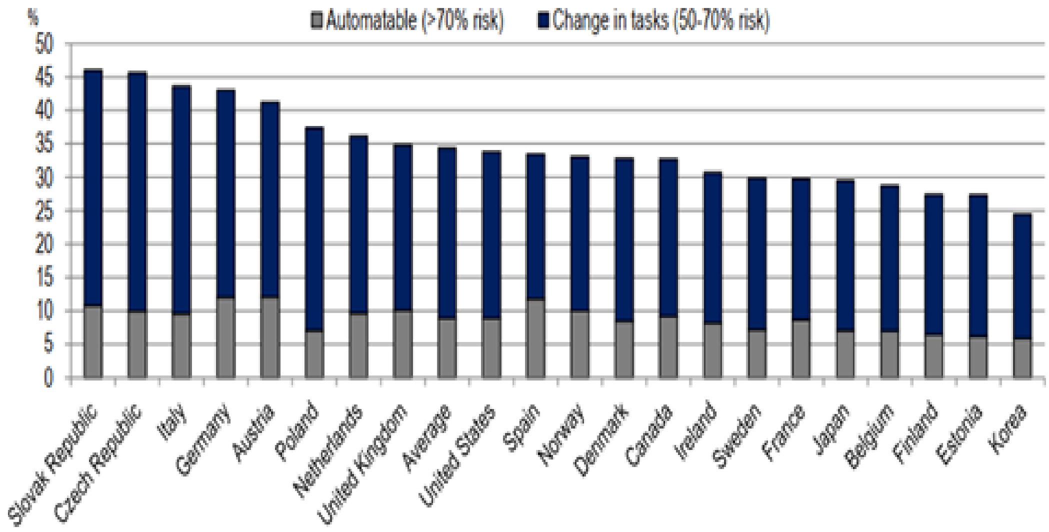
The productivity-enhancing technology causes a decline in the costs of task automation. This would lead to the production of more work as the benefits would be produced even in those sectors that cannot be automated. Moreover, complementary tasks could form new occupations and new activities, through the *spillover effect*: benefits in an economic context occur due to an event in another unrelated context (Vermeulen et al., 2018).

As a consequence, it is expectable to see the creation of new demand, new products and emerging jobs in the entrepreneurial and innovation sectors, where there is a greater demand for high skill work.

The most adverse tasks to automation have proved to be those that require greater flexibility, judgment and common sense, i.e. skills that we only mean tacitly and that cannot be communicated to machines. This is defined by Autor (2015) as *Polanyi's paradox*. For the automation of high skill jobs there would be an objective limit, dictated by the limited ability of the programmer to communicate implicit attributes of human being.

According to OECD (2016) studies, automation will lead to high unemployment rates, but only in the short term, as the risk of losing work is less substantial than many declare. Despite this, many works will undergo a radical change.

*Figure 1.1 Percentage of workers in jobs at high and medium risk of automation*




*Note: Data for the United Kingdom corresponds to England and Northern Ireland. Data from Belgium corresponds to the Flemish Community.*
*Source: OECD, Automation and Independent Work in a Digital Economy (2016, May).*

Furthermore, the output in elasticity of demand combined with the income elasticity of demand could either curb or amplify the effects of automation. In the long run, gains in productivity did not imply a fall in demand for goods and services (Autor, 2015).

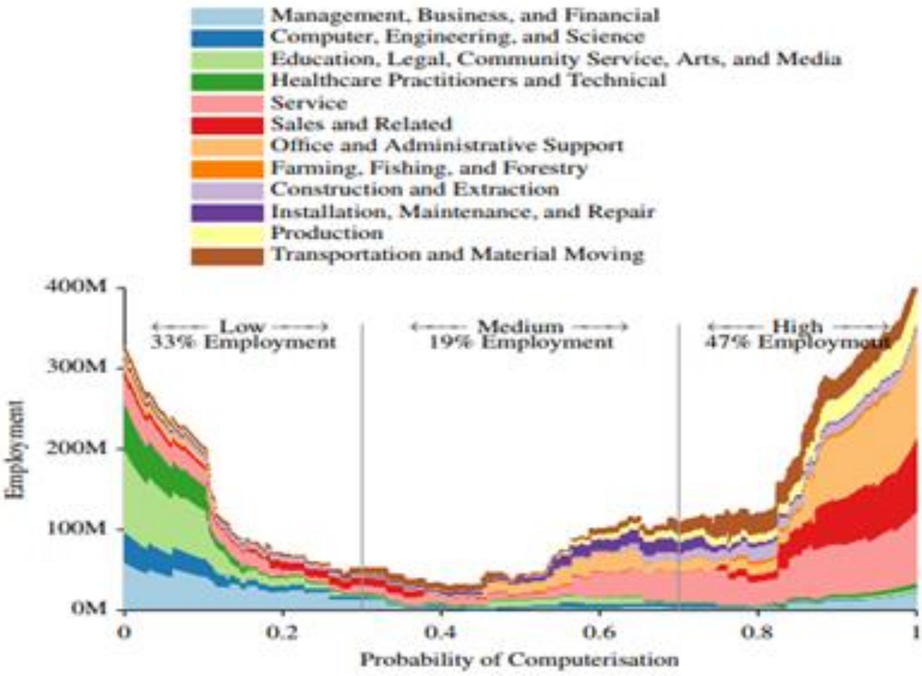
On the other hand, we started to have clear evidence of how computers have already exceeded the limit of performing cognitive non-routine tasks. In the medical sector, computer started to perform diagnostics processing. In the oncology ward at the Memorial Sloan-Kettering Cancer Centre, the IMB Watson computer is used to provide chronic care and cancer treatment diagnostics. By analyzing the history of previous patients, this machine can compare individual symptoms, genetics, medication history, etc., to diagnose the disease and develop a treatment plan with high probabilities of success (Cohn, 2013). It not only aids in conducting diagnosis as it can outperform humans as found by Haenssle, Fink, Schneiderbauer, Toberer, Buhl, Blum, Kallo, Hassen, Thomas, Enk and Uhlmann, (2018) that gauged accuracy in melanoma diagnosis comparing algorithms with 58 dermatologists.

Occupations requiring accurate judgments are becoming more and more susceptible to computerization. In many of these cases, the use of a machine was intended to be an advantage as decisions were not subject to prejudice, however, as seen with Tay bot case (Garcia, 2016) learning algorithms can be intrinsically biased to the point of being labeled as racist or sexist.

The study by Frey and Osborne (2017), on the risk of replacement of 720 jobs, shows that the degree of substitution varies according to two major technological waves. During the first one, we will observe many jobs in transport and logistics being replaced by computer capital. In the second wave, limits of computerization will depend on the overcoming of the bottleneck engineering regarding the creation of a social and creative artificial intelligence. This is already happening (Greshko, 2018).

Consequence of this will be the automation of a large portion of high employment, especially in the services sector.

*Figure 1.2 Jobs probability of computerization*




*Source: C. Frey, M. Osborne / Technological Forecasting & Social Change, 114 (2017) 254-280.*

The factor to be considered is the possible evolution of the technologies that are currently available. According to *Moore's Law* (Ford, 2015), the best-known measure of the advancement of computational power, complexity of a microcircuit (measured by the number of transistors per chip) doubles every 18 months (and quadruples every 3 years). It is therefore difficult to foresee possible limits to the development of new technologies and the areas in which these can replace human work.

*Machine Learning* allows a computer to write a program autonomously through the statistical correlations that it discovers by analyzing data (Lightstone, 2019). *Neural Network* systems are designed using the functional capabilities of the human brain. Still, *Deep Learning System* are programs able to recognize external stimuli and, through an analysis of the same, they can improve this recognition capacity (Ford, 2015): many companies are already focusing on similar *people analytic* systems to improve the recruitment, dismissal, promotion and evaluation of employees. This is leading business to be less dependent from human work, reaching so far better performance, both in automated and non-automated tasks.

But what would this trend entail in macroeconomic terms? The fear that the wave of automation will have negative effects on purchasing power in specific regions is a possibility (Amin & Goddard, 2018).

By considering workers from the consumer perspective, it is reasonable to infer that less work would mean less purchasing power of the middle class which, in the end, is the engine of a country's internal economy (Chun, Hasan, Rahman & Ulubasoglu, 2017). Joseph Stiglitz is perhaps the most active personality in the economic area to support the idea of inequality as toxic term for economic growth (Stiglitz, 2015). Reasoning that over the years we have witnessed an increasing polarization of wealth and therefore inequality, it is easy to conclude that the middle class will not be able to sustain this pace and feed the demand for goods and services forever. The richest percentiles of the population, on the other hand, cannot produce the demand created by the middle class on their own.

If the scenario of job replacement due to automation comes to reality, this trend would be exacerbated and, in the near future, the creation of new demand would be one of the main problems to be faced.

## 1.3. Understanding Human Limits and Behaviors

Getting in touch with the latest discoveries in the field of artificial intelligence, we are overwhelmed by a wave of amazement and fear at the same time. It is natural to question whether the machines are able to match or even to surpass man in the execution of most working practices. If we were to speculate on all the possible future scenarios based on the current knowledge we have, the answer would certainly be affirmative. The limits of artificial intelligences, from a purely mathematical point of view (Moore's law), would seem to be non-existent. But from where we are now, looking too far in the future would be counterproductive.

Much more interesting and useful is to understand which human behavior is more fallacious and where there is more room for a machine to improve our mistakes.

In terms of evolution, what has made us more competitive than other species has been our ability to define our goals, ignoring or filtering when necessary non-relevant external environmental stimuli. According to Gazzaley and Rosen (2016), this feature is called *goal-setting*, which is what allowed us to become skilled at interacting with the surrounding world and to invent complex systems such as language, society and the technologies.

Evaluating, decision-making, organization and planning abilities are triggered by the definition of personal goals. As stated by the two neuroscientists, these goals are generated internally through a *top-down* process, which guides our actions. This path is not completely automated or reflexive, since it activates a series of processes aimed at excluding external interferences (*bottom-up*). This behavioral driving action takes place in the prefrontal cortex of our brain, the place of cognitive activity where a varied set of operations is involved, including goal management. Having goals means managing multiple actions at the same time (multitasking), which requires cognitive activity. Unfortunately, our brain does not process information in parallel, if cognitive control is required. When this activity is involved, a *network switching* process is necessary. During this step, we temporarily interrupt the cognitive activity in progress and we lose accuracy and our performance decreases.

In a reality where we are constantly in contact with external interferences produced by new technologies (smartphone, etc.), our ability to ignore superfluous information requires always bigger efforts. Our distracted mind becomes less and less performing, because it is committed to moving from an activity to another one, trying to ignore the constant exposure to useless information, e.g. as when a notification arrives on our smartphone while we are driving (Gazzaley & Rosen, 2016).

Furthermore, we are implicitly attracted by the constant availability of new information. We cannot deploy our attention for a long time on a task since we are incentivized to change and focus on something else, probably less relevant. Pirolli and Card (1999) explained this dynamic by applying the MVT (*Marginal Value Theorem*) model to human behavior regarding the transition from one piece of information to another.

The MVT model has been used to explain why animals prefer to change the source for food supply: when in a tree the acorns begin to run low, for a squirrel it is more convenient to move to a new tree full of acorns with higher marginal value. Here, searching for food will be faster and less expensive. The human being behaves similarly with information. Full availability of apparently more palatable information prevents us from spending too much time on the source we are analyzing. This affects our ability to explore or perform certain tasks, making us more inaccurate and less efficient.

This alteration of our ability to consider the information costs/benefits is influenced by several factors: boredom, anxiety, accessibility and lack of understanding our mind functioning (metacognition problem) (Gazzaley & Rosen, 2016).

Speaking of modulation of human cognitive processes, we need to mention the work of the two psychologists Daniel Kahneman and Amos Tversky, who have enriched the *two systems* concept with brilliant arguments.

- *System 1* operates automatically, quickly, does not imply any effort and does not need any voluntary control.
- *System 2* needs attention, cognitive effort, calculation, concertation and reflection.

Being faster, the System 1 is also the fallacious one, since it operates through prejudices, heuristic, stereotypes and shortcuts. System 2, on the contrary, is more accurate and effective, but it is also lazy and to be activated it requires a series of cognitive efforts (cognitive strain).

Given this lack of practicality, due to a logic of mental economy, individuals in most of their behavior rely on System 1. Their behavior is therefore prone to systematic and recurring errors (Kahneman, 2011). It is redundant to say that machines do not need to apply this type of economy, since their activity is constant and does not undergo alterations.

Furthermore, Richard Thaler (2017) differentiating between *Humans* and *Econs*, theorized how human decisions are basically erroneous, because they depend on some fallacious mental processes, e.g.:

- *Halo effect*: the first impression is the one that leads to full evaluation, even if this impression then appears to be wrong (Kahneman, 2011).
- *Prospect Theory*: decisions depend on the context (*framing*) in which they are taken, on the disposition and availability of information and on the psychological weight that the subject gives to each element (Tversky & Kahneman, 1992).
- *Reference points*: decisions are made based on pre-existing reference points in the subject, such as mental anchors. These lead to a cognitively simpler choice to take but lacking an appropriate cost/benefit assessment (Kahneman, 2011).
- *The Endowment Effect*: in an economic choice, excessive value is given to a value possessed, therefore we are not inclined to make a profitable exchange when it implies its loss (Kahneman, Knetsch, & Thaler, 1991).

If we compare the limits of human behavior with the development of new technologies, we note that these limits will most probably be cut down and overcome by the automation of daily activities.

The latest technological discoveries have largely changed the non-routine tasks in well-defined problems: e.g. Google Translate, which is now able to instantly translate long texts in various languages with better and better degree of accuracy (Frey & Osborne, 2017). The new algorithms, with the help of big data, can refer to millions of resources to obtain the information necessary to carry out these activities and improve along the way. All this left behind classic and banal mistakes made by the human being.

All things considered, we are clearly facing a turning point that will have a significant impact on the various segments and sectors of labor market. Now it is up to us to understand how to take advantage and make these changes profitable. A key to achieving this goal will undoubtedly be to understand the degree of workers' acceptance in regards the use of these intelligent machines, that are objectively better than humans in performing their work, especially from a cognitive point of view. To understand this will probably shed light on the most appropriate way to implement this change, in a both social and economic sustainable way.

# 2. e-HRM – the role of digitalization in Human Resources Management

## 2.1. Current situation and challenges ahead

At this point, it is important for us to identify and describe the concept of e-HRM. This term stands for electronic Human Resources Management and scholars took time to properly identify it. After years of discussions, in 2009 Bondarouk and Ruël came out with an official definition of e-HRM:

‘‘*an umbrella term covering all possible integration mechanisms and contents between HRM and Information Technologies aiming at creating value within and across organizations for targeted employees and management’’* (Bondarouk & Ruël, 2009).

Therefore, we can consider all web defined method, digitalized and IT tools as parts of the engineering of e-HRM. Starting from the HR it aims to create value in the whole company, since the effects of digitalized HRM reflects on others sectors as well. In the same year, a second definition embraced human resources information system (HRIS), which magnitude was restricted only in HR department, without any extension on the outside.

This is the main difference between the two terms: while HRIS is intended to improve the methods and processes strictly within HR, e-HRM main challenge is to enhance the performance of workers in general, giving more value to HR as a strategic sector in the composition of the organization (Hussain, Wallace, & Cornelius, 2007).

Some researches gave an empirical evidence in contrast with this assumption. Ball (2001) proved that e-HRM is mostly used for routine administrative task in more than 50% of the cases. Haines and Lafleur (2009) stated as well that e-HRM practices are applied more for administrative goals than for analytical or strategic ones.

For sure, we can clearly identify the benefits that an organization capitalizes by implementing e-HRM. Either we conceive the application of e-HRM both from the strategic point of view or from merely administrative tasks, we can testify a facilitator effect in work conditions (e.g. support users, high data quality, compliance, policy practice alignment) which brings to directly create additional value to HR (Ruël & van der Kaap, 2012).

We cannot forget that in recent time, the role played by Human Capital Management is becoming critical, especially since the increasing wave of externalization of services and of the offshoring business dynamics.

Enhance the effectiveness and improve the quality if HRM is nowadays fundamental to ensure a strategic advantage to any company. In this scenario, e-HRM has the role to speed up velocity of information flows and to handle efficiently multiple processes, becoming central in the dynamization in decision-making. Integrate HR with new technology helps in leveraging the HR activities, automating transactions and processes. This, of course, has a positive impact on efficiency but it contributes to a main change in all HR practices as well, developing a complementary function (Varma, 2011). e-HRM ensures easier, faster and cheaper HR activity accomplishment, helping to take more effective strategic decision to solve HR problems (Roman, 2017).

Since we can see that e-HRM definition expands to all sectors within the organization, here is where the biggest challenge for electronic human resources management dwell: establish a primary role in non-HR department. With information technology HR services can be delivered in an easier way and outside the organizational boundary, to different groups of users from senior management to non-managerial employees (Bondarouk, 2014). Having this in mind, we can easily describe another role of e-HRM, which is not restrained purely to cost-benefits side, but embrace and build up a new management system.

Overall, it is possible to recognize three types of e-HRM practices in terms of their potential goals: operational, transformational, and relational. Operational practices are the ones which focus in the administrative area of HR (e.g. time management, personnel administration and payroll). Here digitalization has the main role to improve efficiency. On the other hand, computerization of transformational HRM aims to strategic orientation improvement (Panos & Bellou, 2015). In regards the relational side of e-HRM, it has been largely described (Bissola & Imperatori, 2014) that employees' attitude is influenced by HR practices and by their perception of HR systems. Through e-HRM practices, the organization can favor transparency about HR policies, which will bring benefits on the workers' perception of procedural justice and in their trust on the organization. e-HRM can also improve the intelligibility of working relationship, performing as a strategic partner in reinforcing trust in HR department and in fostering its credibility (Graham & Tarbell, 2006).

Of course, this enrichment in trust and credibility is neither linear nor granted, but it depends on the users' acceptance of e-HRM applications, which plays a crucial role between technical implementation and organizational effectiveness (Bondarouk, 2014). Is therefore inevitable to depend the concept of users' attitude towards e-HRM.

## 2.2. Attitude towards e-HRM

The attitude users have in regards technology, specifically in e-HRM, has been object of discussion for decades. Employees' perception of e-HRM must always been considered when a company decides to implement new tools which imply a redefinition on HR roles.

In this field, the most known model is probably the *Technology Acceptance Model* (TAM) (Davis, 1989), which defines a theory of the acceptance and attitude towards IT system, describing attributes that are highly influential in users' behaviors. It is possible to consider *experience ease-of-use* and *experienced usefulness* the two most important factors, which are directly proportional in influencing positively employee acceptance.

Ulrich (1997) *role of HR function in the organization* model is also suitable to derive some considerations about attitude towards new technologies in HR. The author defined four roles played in HR within companies. The first one is the "strategic partner" which is responsible to define company policies and to harmonize processes. The second role called "change agent" is appointed to drive the organization through changes according to long-term objectives. The third role, the "administrative expert", is responsible to look and carry on the operational day-to-day work in HR, assuming in the long run a more strategic part in administrative transactional process. The last role the "employee champion" is based on short-term problem solving and in support both employees and managers in daily activities.

According to Gardner et al. (2003), it is possible to observe a positive attitude towards e-HRM especially in the change agent and strategic partner roles. This is expectable because people in HR playing these roles can take advantage of benefits derived from digitalization of operational task to focus more on strategic activities. Conversely, people in the remaining roles show aversion to e-HRM processes, because they lead to a loss of personal contact between employees, which is considered critical in carrying on their activity.

Voermans and van Veldhoven (2007) added other control variables to the equation of the attitude towards e-HRM, such as tenure in a company, job experience, job type, age, gender, general IT knowledge, and organizational branch (functional area). Not all this variables were considered relevant, since an important relation was found only for the branch within the organization. Only two variables positively mediate the process that improved attitude towards e-HRM: positive experiences with an IT system, and the employees' preferences to the role played by HR in the organization (Voermans & van Veldhoven, 2007).

It is worth to mention the empirical analysis conducted by Yuslizaa and Ramayah (2012) which explores the impact of e-HRM goals clarity, user satisfaction, perceived usefulness, perceived ease-of-use, user support, social influence, and facilitating conditions on attitude towards using e-HRM. The research reported strong correlation between all variables, which suggests they all should be considered as determinants for HR professionals to define their attitude in using HRM technologies.

Another critical element is the impact of the IT technologies implementation in HR on employee satisfaction. Boudreau and Robey (2005) found that the impact of the digitalization in HR can affect both job satisfaction and turnover intention. Skills in operating in new systems interplay a strategic role, since the success or failure of the implementation of new technologies depends on these skills (Panayotopoulou et al., 2007) which may also restrict the full potential utilization of IT tools in the case of unskilled employees (Lukaszewski et al., 2008).

These limitations in technical knowledge may lead to a negative evaluation of the new technology. On the contrary, knowledge of the system can bring facilitation in usage, and thus favor a positive perception on the HRIS.

In general, the attitude towards organizational changes may impact job satisfaction, turnover intention, and voluntary turnover. Communication regarding the reason of these changes can influence employee perception on new e-HRM systems and, therefore, could improve or deteriorate their disposition. When the new IT is perceived as threating, employees satisfaction declines and turnover intention increases. This manifests as consequence of a failure of the organization in creating a positive image of the new changes (Maier et al., 2012). The bottom line idea from extant research is that HRM transformation in companies do have individual work-related consequences.

Building from this idea, the key to successfully implement e-HRM lies in developing employees' trust in technologies and AI.

## 2.3.Developing Trust in machine and Artificial intelligence

Acceptance of new technologies can be influenced by trust, since this variable is crucial in all kind of relationship, be they human-social interaction or virtual interaction (Xin et al., 2008). *Initial trust* refers to trust built based on individual disposition or institutional cues (McKnight et al., 1998) and plays a centric role when it comes to implement new technologies. In most of the cases trust is built gradually and it can be considered as *continuous trust*. When it comes to study AI, both variants of trust should be taken in consideration (Siau & Wang, 2018).

Considerations of utility are important to understand acceptance of new products/tools but these considerations should be embedded in the social context where trust can develop (MacVaugh & Schiavone, 2010).

According to Mayer (1995), in interpersonal relationship, trust represent the willingness to be vulnerable to the action of another person, this is essential for reducing the perceived risk (Rousseau et al., 1998), which, in a context of AI and new technologies, results from the delegation of part of one's own control to a machine (Castelfranchi & Falcone, 2000).

In the case of radical new technologies, the importance of initial trust is critical, since the perception of risk must be surpassed creating the willingness to use (McKnight et al., 2002). In early phases, predictability of technologies influences trust, which can be defined as the possibility to anticipate their future behavior (Hengstler et al., 2015).

It is a general mistake to believe that quality of technological innovation is enough to bring people to use a product (Slater & Mohr, 2006). There will always be skepticism from users, which must be handled during the implementation of this kind of change. Skepticism most probably emerges when an application takes the place of human decision-making, using for example machine learning or AI (Lee & See, 2004).

Operational security and data security are also decisive factors in developing trust in a technology. Users perception of their own safety is fundamental being a necessary but not sufficient condition for user's acceptance (Hengstler et al., 2015).

Cognitive compatibility, trialability and usability are determinant in building trust as well. Cognitive compatibility can be defined as the alignment between what people think about an innovation and their values. Usability is influenced by both the intuitiveness and mediation effect on human-machine interface. People are more willing to accept a new technology if they perceive it as an assistant than as an invasive application (Hengstler et al., 2015). This mediation effect is mostly important when it comes to AI, since its objective is to indirectly influence human behavior by improving human communication, conditions and actions.

Contextualization of an application has also a significant impact in building trust: locating a tool in a specific context helps to avoid generalization of the technology itself. These features, together with communication, influence social acceptance. Therefore, open and proactive communication can increase credibility and trust towards new technologies and have positive impacts on attitude as well (Hengstler et al., 2015).

According to Siau and Wang (2018), to develop trust in AI we should consider several points which need to be improved: 1) First, since AI has the potential to surpass human performance and replace several activities, people can perceive it as threat. Therefore, it is important to make AI scope congruent with human goals and create the basis for developing future trust. 2) Additionally, we should consider sociability and bonding. Continuous trust cannot go alone, it has to match with social acceptance, since it is most likely that in a near future, these technologies will be more and more integrate in our lives in both practical and social aspects.

We clearly see that trust will be fundamental for successfully implementing new technologies, and several variables should be taken in consideration. Trust is not a static process, but it involves changes and dynamic trends. In the case of AI, it is critical to question whether trust has been built beforehand and understand how this can influence the success or failure of a technological investment.

# 3. A Predictive Model for Skills Enhancement and Job Replacement

## 3.1. Skills in e-HRM

So far studies which aimed to understand the magnitude of job replacement caused by automation, focused their attention on substitution of tasks (Autor 2015, Dengler & Matthes, 2017; Vermeulen et al., 2018). Taking distance from this conception of job replaceability merely based on tasks or functions, we moved forward involving skills in our analysis.

According to Cambridge Dictionary, "skill" is defined as the ability to do an activity or job well, especially because one has practiced it. Likewise, competence is termed as the ability to do something well. Some authors (e.g. Bartram & Roe, 2005) attribute to competencies a wider meaning: a learned ability, which is built upon knowledge, skills, personal values and attitudes and therefore incorporate all those elements. For the interest of our research, we will consider skills and competences as synonyms. Additionally, to consider skills a static construct would be a mistake, since automation may conduct to important adjustment in business competences demand (World Economic Forum, 2018) and, consequently, to a concept redefinition of skills.

Skill encompasses many possible variables although there is a structured body of knowledge that consider cognitive, psychological and interactional aspects, as well as functional ones, deployed during the work activity. The multi-factor model proposed by Meriac et al. (2014) establishes varying degrees of depth in analyzing skills. At the 3-factor level, the authors identified technical (or administrative) and social (or relational) skills. Whereas administrative skills are clearly related to cognitive ability, relational skills should be more strongly related to noncognitive variables. The original model includes a component which is used to measure endurance and positive or negative energetic boost in performing daily activity: *Drive.* Several elements are considered int its scope, such as: career ambition, energy, initiative, job motivation, tenacity, work standards perception.

It is extremely relevant to include in our considerations another main category, which we will consider as *meta-skills*. These comprehend all those skills generated through *meta-cognition*, meaning the knowledge about one's own cognition and regulation of that cognition activity. In this context, regulation stays for executive planning, monitoring and evaluation of the performance of a task. Meta-cognition embraces strengths and weaknesses, learning strategies, and monitoring learning (Billing, 2007).

Lastly, approaching Meriac et al. (2014) six-factor level one should consider O*NET (Onet, s.d.). Other skills include characteristics and limits of human behavior, both due to neurological and psychological perspective (Gazzaley & Rosen, 2016; Kahneman, 2011; Sussner, 2000). Moreover, *Empathy* (Davis, 1980) may be considered a critical feature in social exchanges.

Overall, from Thaler (2015), Meriac et al. (2014), Kahneman (2011), Gazzaley and Rosen (2006), Sussner (2000), Kahneman, Knetsch, and Thaler (1991), Davis (1980) and O'Net (sd) we identified 15 major skills, as follows:

1. *Goal Setting* (Ability to filter and organize information to define one's own objectives, Gazzaley & Rosen, 2016);
2. *Integrity* (Performing honest and ethical behavior contextualized to specific work environment and situations, Meriac et al., 2014);
3. *Problem Solving* (Capacity to handle situations and to solve problems in complex, real-world settings, Onet, s.d.);
4. *Resource Management Skills* (Capacity to allocate resources efficiently, Onet, s.d.),
5. *Social Skills* (Capacity used to work and interact with people to better achieve goals, Onet, s.d.);
6. *Technical Skills* (Capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems, Onet, s.d.);
7. *System Skills* (Capacity to understand, monitor, and improve overall systems - this includes system analysis and evaluation - Onet, s.d.);
8. *Autocorrection Skill* (Ability to identify and correct one's own systematic and unconscious errors - in humans this regular misbehave derives from usage of *System 1* in carrying on most of our daily activities, Kahneman, Knetsch, & Thaler, 1991; Kahneman, 2011; Thaler, 2015);
9. *Learning Capacity* (Ability to acquire knowledge to improve one's own work processes to enhance job performance, Onet, s.d.);
10. *Planning and Organizational Skills* (Capacity to control/delegate subordinates, organize resources to better achieve goals and to plan work activity accordingly, Meriac et al., 2014);
11. *Group Empowerment Skills* (Ability to enhance one's own work by interacting with others and improve jointly the quality of the group itself, e.g. Team or network of machines, Meriac et al., 2014);

12. *Communication Skills* (Capacity to clearly communicate implicit and explicit messages, Meriac et al., 2014);
13. *Empathy* (Ability to understand the other's point of view in an accurate way (Davis, 1980);
14. *Influencing others* (Ability to persuade others to do something they otherwise would not do, Meriac et al., 2014; Onet, s.d.), and
15. *Intuitive Ability* (Capacity to deduce complete patterns from partial information, Sussner, 2000).

Skills enable us to look at the sociological and psychological side of the relationship with machines. Comparing the performance of certain human skills with a machine or AI, allowed us to relate such competences to a non-human element and therefore evaluate which one is better.

Integrating the model suggested by Maier et al. (2012), which analyzed the relationship between attitude towards HRIS and turnover intention mediated by job satisfaction, we elaborated our first hypothesis:

*H1: Overall job substitution by machine and AI will mediate the positive relationship between perceived workers' skill replaceability and attitudes towards AI in e-HRM and a-HRM.*

## 3.2. Trust as a moderator in attitude towards AI in e-HRM

Since we are talking about skills, we could move from a functional context towards an inner perception, which involves *Trust* or *Mistrust* in machine and AI as a social and economic sustainable investment in e-HRM.

Is it possible to trust in a component, which we perceive as outperforming us in several aspects? Should we be worried about job replacement, i.e. that in the future no more human effort may be required? Or that those organizations who resource to human work may fall short from the efficiency and effectiveness of their competitors that opted not to?

To consider our skills and establish to what extent technology offers better solutions is for sure a good trigger to stimulate a concrete reflection in this regard. These considerations are relevant in a context where trust in technology can represent success or failure in the investment on automation and AI (Siau & Wang, 2018).

If trust is solid and deeply placed in a new tool or technology, then it will be easier to implement it and workers will be more willing to cooperate with it (Xin et al., 2008).

When it comes to AI, trust may be weakened. As mentioned, the types of innovation brought by the fourth industrial revolution are overturning the concept of human work (Ford, 2015; Schwab, 2016).

It is easy to imagine that, according to the speed of these innovations, the most of human skills will be easily substituted my machines and AI. Right now, in order to compete with human intelligence, the limits machines have to surpass are enormous, but even if technical evolution overcomes this challenge, the perception of workers about their own skills weaknesses and their possible demise must be considered to ensure social and political sustainability about implementing AI-based automation.

Probably, the elapsed time humans have been in direct contact with AI-based machines is not enough to trigger relevant behaviors that may produce a shared social judgment about AI technologies. We should consider that the impact of AI on the labor market did not fully come forward yet and in order to gauge its effect in concrete we may still have wait some years until it reaches the critical mass for a systemic impact.

We believe that perception of one's own skills replaceability by machine and AI influences the attitude in accepting and working with these technologies. Now, if this influence is positive or not may depend on the level of trust placed in AI.

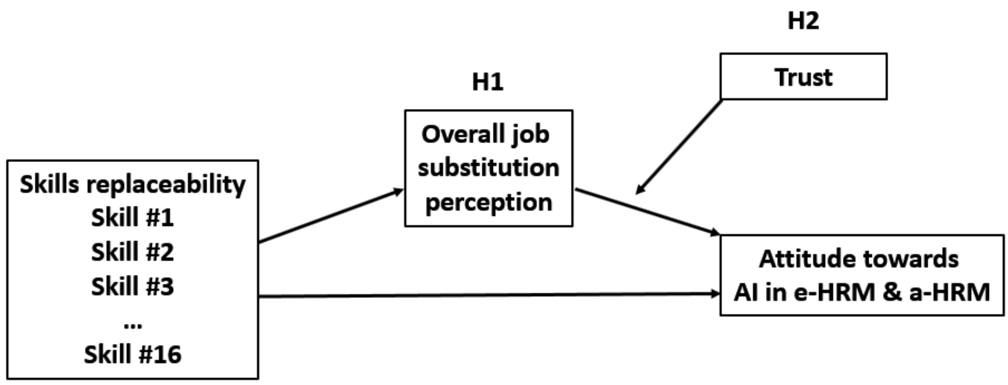
Approaching the question from logical, psychological, sociological, economics and even Darwinian point of view, would lead us to a simple resolution: if we feel to be substituted by a new component, we should be afraid of it and fight to preserve our role/place in society. The only thing that can interfere in this dynamic is the belief that these changes are good for our "species" and that they can overall improve our lives and status. As already mentioned in the previous chapter, people are more willing to accept a new technology if they perceive it as an assistant than as an invasive application (Hengstler et al., 2015). This mediation effect is mostly important when it comes to AI, since its objective is to indirectly influence human behavior by improving human communication, conditions and actions.

Since we are discussing on events and implications that will display their full potential and effects only in the near future, a positive attitude should be generated by strong trust in these innovations. Following these considerations, we formulated the second hypotheses which adds the first one by previewing a moderation effect from trust, as follows:

*H2: Trust will moderate the indirect effect between perceived skills replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception, in such a way that the indirect effect is stronger as trust increases.*

According to these considerations and in line with our results, we have developed the following theoretical model (Fig. 3.1):

*Figure 3.1 Skills replaceability and attitude towards AI in e-HRM and a-HRM*




In the lower part of the model it is represented the direct relationship between perceived workers' skills replaceability and attitude towards AI in e-HRM and a-HRM. Our initial expectation was that the two variables would have been inversely proportional related: if one is positive the other should be negative. So, for high perceived skills replaceability, the attitude towards the implementation of this kind of technologies would have been more hostile. Such statement derives from our initial consideration: if someone feels that his/her own competences may be substituted by and algorithm, machine or electronic device, then it would be possible to be against the implementation of these technologies, because of the fear to possibly loose the job in the near future.

Likewise, in the upper part of the model it is depicted the mediated relationship between perceived workers' skills replaceability and attitude towards AI in e-HRM and a-HRM, mediated by overall job substitution perception. Additionally, during the mediation in the second step of this path, it is shown the moderator role of trust on the relationship: for higher level of trust we expected more positive attitudes towards AI.

To base our model with concrete data, we did feel appropriate to opt for a quantitative empirical research, as described in the method section.

# 4. Method

## 4.1. Research design

The method has been structured on a quantitative empirical research based on a questionnaire (*Appendix A*) built upon our theoretical model *(Fig. 3.1*). We could have opted for an inductive approach, but we contend there is already a sufficient body of research that enable a hypothetic-deductive approach. It also enables future researches to explore qualitatively some possible findings to build theory on *a-HRM* (*automated HRM*). At this phase, the variables in interplay are many and a qualitative approach without more solid objective ground could probably offer an overly subjective view.

## 4.2. Data analysis strategy

By following recommendations by Hair et al. (2010) we processed the data to detect and remove outliers, errors and deal with missing values. Missing values were found only for "Education" and "Company size", and their low frequency advice keeping them in the database instead of replacing by series means, which would bias true data (some missing values simply correspond to "not applicable" such as in the case of students). After having the databased screened we ran psychometric tests to check the validity of the constructs by means of factor analysis-exploratory or confirmatory depending on pre-existing theoretical structure of the constructs (Schreiber et al., 2010) as well as reliability (Composite reliability - CR, with the minimum threshold of .700) (Santos & Reynaldo, 1999). Confirmatory factor analysis model fit was judged with Hair et al. (2010) recommended indices and respective thresholds as follows: $\chi 2/DF$ below 3 with a statistically non-significant p value ($p<.05$), plus Comparative Fit Index (CFI) $\geq .95$, Tucker-Lewis Index (TLI) $\geq .95$, and the Root Mean Squared Error of Approximation (RMSEA) $\leq .07$. Following Hu and Bentler (1999).

Finally, we proceeded to descriptive statistics and built the bivariate correlations table. Because of relatively modest sample size (N=184) we opted to conduct hypothesis testing via PROCESS Macro built in SPSS 25 (Hayes, 2013) to test the moderated mediation model. This program conducts bootstrapping analyses that generate lower and upper bounds for a bias corrected interval defined by the user. We set the recommended number of repetitions to 5000 and the confidence interval at 95% (CI95). Any given effect is statistically significant for this CI95 if the lower and upper bounds do not cross the value "zero".

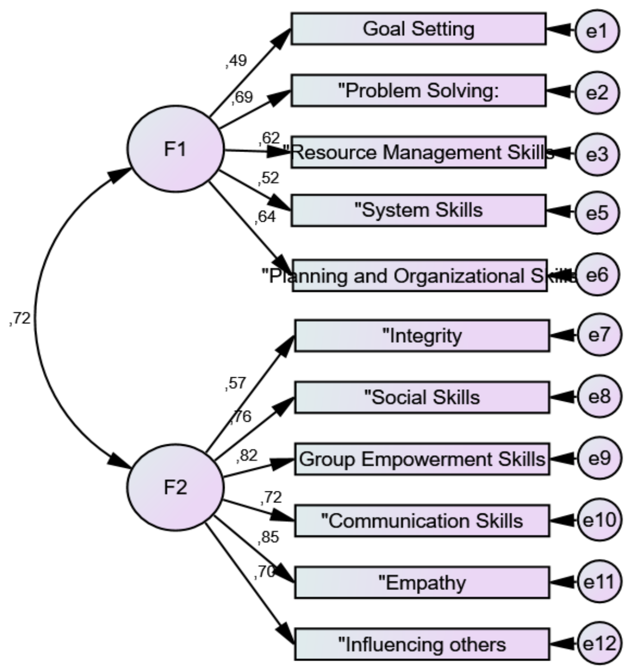
The model obtained corresponds to *Model 14* proposed by Hayes (2013) and it describes the mediated relationship between four variables: 1. *Skills replaceability*; 2. *Substitution perception*; 3. *Trust*; 4. *Attitude towards AI in e-HRM and a-HRM*.

## 4.3. Measures

**Skills replaceability** was measured with 15 items comprehending all previously described skills. The respondent was requested to answer using a 10-point Likert scale ranging from 1 (*fully irreplaceable by machine*) to 10 (*fully* replaceable).

The skills are theoretically expected to aggregate around two major domains: technical and social. Technical skills comprehend six items (goal setting, problem solving, resource management skills, technical skills, system skills, and planning & organizational skills). Social skills comprehend six items (integrity, social skills, group empowerment, communication, empathy, and influencing others). A confirmatory factor analysis for this two-factor solution showed acceptable albeit suboptimal fit indices ($\chi^2$/DF=2.053, p<.001; CFI=.932; TLI=.915; RMSEA=.076). Due to a low factor loading of one item and deducing from Lagrange Multipliers we have excluded one item (Technical Skills) which translated into a substantial improvement of the model ($\chi^2$/DF=1.491, p=.020; CFI=.972; TLI=.965; RMSEA=.052). This improvement is statistically grounded as showed by the $\chi^2$ difference test ($\Delta\chi^2_{(10)}$=44.689, p<.001) and we interpret it as signaling an overarching category that applies to all the remaining technical skills. These factors are also reliable ($CR_{technical\_skills}$=.732, $CR_{social\_skills}$=.879). Psychometric findings thus encourage the use of these two factors in ensuing analyses.

*Figure 4.1 Two factors analysis*




The remaining three items concern meta-skills as stated in the previous chapter. They can be taken as isolated constructs that correspond to higher cognitive processes that focus not on an external object but rather on the individual him/herself. These are: intuitive ability, learning, and self-correction skills.

Lastly, all the relationships examined during the current study included variables which were obtained from the same source (i.e. employees) and data collected during the same period, which creates an opportunity for common method variance (CMV) to occur (Podsakoff et al., 2003). In order to test empirically CMV and to avoid its threat in our results, we followed Lindell and Whitney's (2001) marker variable procedure. According to these authors, a marker variable is a variable collected at the same time and in the same manner as focal variables, but that is not theoretically related to them. Consequently, we have also included item nr. 16, the *Drive* component (Meriac et al., 2014) as a measure to compare and weigh human endurance to that of machines. We do think this does not meet Bartram and Roe's (2005) criteria to qualify as a competence. Machines (computer, robot etc.) will endure 100% level of energy in the full period while humans have some restraints and obstacles in full performing their activity for a prolonged period. These limits are characterized by fatigue, lack of motivation, low work standard perception etc. On the other hand, in human behaviors there may be factors that act as a boost for performance, such as high motivation, job satisfaction, good work environment, higher objectives to achieve etc. Balancing these points, we asked to our respondents how much they estimated that human drive could match machine performance. We opted to include this variable in the design because it is usefully employed as a marker.

Also, in this case, we have measured the item using a Likert scale, that started from point 0=*human cannot match machine performance (0%)* to 10=*Human fully match machine performance (100%).*

**Overall perceived substitution** was measured with a single item (nr.17) that was framed under the question: "*Do you think that much of the work currently done by humans will in future be substituted by machine*?". Participants were invited to answer in a 4-point scale to which degree they believe this was probable or improbable as follows: 1. "*This will definitively happen";* 2. "*This will probably happen";* 3. "*This will probably not happen"; and* 4. "*This will definitively not happen".* As a detail request from this question, the participants were also invited to state (item nr.18) in percentage terms, from 0=*Almost none of human work will be replaced by machines (0%)* to 10=*Almost all human work will be replaced by machines (100%)* their quantified expectations.

**Trust in machines and AI** has been retrieved from the answers to the question (item nr.19) "*How much do you trust the investments in automation through machines and AI, as a measure to help workers in their daily activities?*". The responses were categorized trough a 10-point Likert scale where 1="*I totally don't trust"* to 10="*I totally trust".*

**Attitude towards AI in e-HRM & a-HRM** was measured by the question (item nr. 20) "*If you were a decision maker in a big company…From 0% to 100%, how much would you think should your company invest putting AI inside HRM making it automated, electronic and digitalized?*". Participants were expected to answer by means of a Likert scale where 0="*I wouldn't implement this kind of investment (0%)"* and 10="*I would be totally in favor of this kind of investment (100%)".*

**Sociodemographic** information was collected both for descriptive and control purposes. This included 6 items concerning: *Age, Education* (field of study and educational level – 1=undergraduate, 2=BSc, 3=Master, 4=PhD), Gender (1=Female, 2=Male), Size of company (1=Small, 2=Medium, 3=Large), Occupation (dummy coded for HR occupation 0=No and 1=Yes, and IT occupation 0=No and 1=yes), and familiarity with AI asking "*How much are* *you familiar with the concept of AI (Artificial Intelligence)* answered from 1= "*I have no idea of what AI is*" to 10= "*I'm fully aware of the new technologies and possibilities*".

## 4.4. Sample

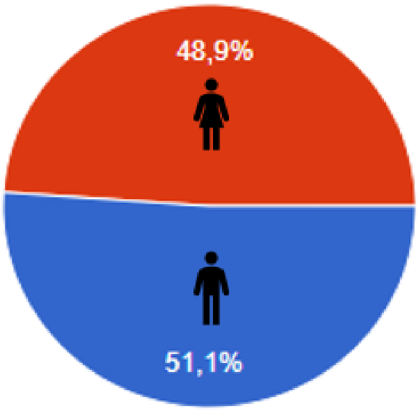
As the subject is relevant for all population, we opted not to restrain the sampling procedure to a specific segment. However, as the HR and IT related questions are better suited for those working the area, we pushed to guarantee a sufficiently large representation of these professionals in our sample, by a snow-ball procedure targeting professional networks (LinkedIn). Publishing the survey on Linkedin enabled to reach mostly white collars and to have a higher educated sample, purposively so to avoid the lack of understanding risk with respect to some terminology used in the questionnaire. This strategy, of course, influenced also the output of our research: higher educated people or workers with familiarity with IT and AI tools, have most probably a different perception and opinions about automation and job replacement, comparing with blue collars.

White collars are now the largest target of job substitution by intelligent machines in the same way blue collars were in recent industrial past.

Our purpose was to favor the most comprehensive sample possible, although we do acknowledge the sampling procedure does not follow a random process. So, external validity caveats must take place when interpreting findings.

Overall, the sample is composed by 183 people. Among these 94.5% report being under a paid job, all the participants are white collar and aged between 17 years old and 63 years old, averaging 33 years (sd=8.1). The sample is gender balanced with male respondents comprehending 51.1% of the sample (Fig.4.2).

*Figure 4.2 Gender distribution*

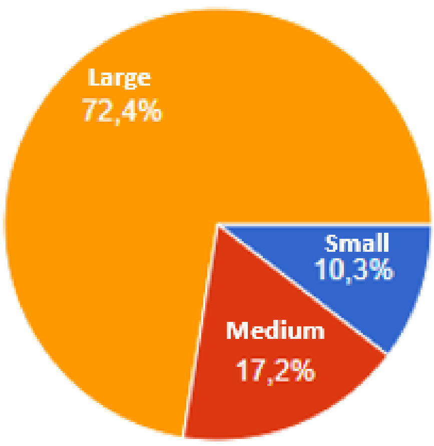



As stated, our sample is composed mainly of highly educated people (tertiary education): we have just four cases of workers with secondary school level (inferior to bachelor's degree). The rest is divided in 86 people with bachelor's degree (47% sample), 90 with master's degree (49% sample) and 3 with PhD (1.6%).

The sample comprehends a diversified work function description. The most frequent occupations fall in the IT domain (n=30), HR (n=64), engineers (n=7) and managerial roles (n=33). It is important to mention that these job functions are not mutually exclusive (e.g. we may have a person which works in IT side of Human Resources with middle management responsibility and so, the sample comprehends 23 cases of individuals working both in HR and IT).

With respect to the size of their organization, we have 72.4% participants reporting to work in a large company, 17.2% in a medium sized company and the remaining 10.3% in a small one.

*Figure 4.3 Distribution per company size*



Due to the nature of the subject, it was important to differentiate our sample regarding the level of familiarity with the concept of AI. This element is crucial for us to understand if respondents feel comfortable enough to report being aware of AI technologies, the possibilities of their application and how this eventually influenced their answers. As stated, the scale ranged from 1 (I have no idea of what AI is) to 10 (I'm fully aware of the new technologies and possibilities) and our sample reported a mean of 6.9 (sd=1.8), suggesting that large majority of participants think to have a good understanding of AI dynamics and its implications.

# 5. Results

This chapter is organized in order to show descriptive and bivariate statistics followed by hypotheses testing. Because the predictor in the model covers six possible variables (technical skills, social skills, intuitive ability, learning, autocorrection, and drive) we conducted twelve independent mediation models, moderated models tests with Process Hayes (2017) model 4 and 14 (six tests for each model). Model 4 has been used to test the mediated positive relationship between perceived workers ‘skill replaceability and attitude towards AI in e-HRM and a-HRM. Likewise, model 14 has been applied to test the indirect effect from overall job substitution perception by machine and AI to attitude towards AI in e-HRM and a-HRM, considering trust as moderator in this relationship.

## 5.1. Descriptive and bivariate statistics

Table 5.1 describe the statistics for N, minimum and maximum value, means and standard deviation as well as bivariate associations.

Overall, respondents report to be familiar with AI and perceive technical skills replaceability as more probable (M=6.59) than social skills replaceability (M=4.28) judging on paired t test ($t_{(182)}$=18.687, p<.001) corresponding to a bootstrapped 95CI of difference [2.064; 2.551]. Likewise, intuitive ability is seen as harder to replace (M=6.10) than technical skills ($t_{(182)}$=2.709, p<.01; CI95 [0.130; 0.831]) and auto correction ($t_{(182)}$=-5.431, p<.001; CI95 [-1.542; -0.720]) but easier than social skills ($t_{(182)}$=9.756, p<.001; CI95 [1.457; 2.196]) and equivalent replaceability of learning capacity. As regards learning capacity it has the equivalent average of technical skills and it is easier to replace than social skills ($t_{(182)}$=14.217, p<.001; CI95 [2.441; 1.846]) but harder than autocorrection skills ($t_{(182)}$=-4.093, p<.001; CI95 [-1.206; -0.421]). Lastly, autocorrection skills are taken as easier to replace than both technical skills ($t_{(182)}$=3.965, p<.001; CI95 [0.326; 0.973]) and social skills ($t_{(182)}$=15.301, p<.001; CI95 [2.576; 3.339]). Overall autocorrection skills are perceived as the most easily replaceable and social skills as the hardest. In the middle lies technical skills, learning capacity and intuitive ability from the easier to harder to replace, respectively. Considering the averages, only social skills fell below the midpoint of the scale.

*Table 5.1 Descriptive and Correlations*

| N=183 | min-max | mean | sd | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Gender | 1-2 | NA | NA | - | | | | | | | | | | | | |
| 2. Age | 17-63 | 32.8 | 8.11 | .245** | - | | | | | | | | | | | |
| 3. Education | 1-4 | 2.51 | .57 | -.073 | -.139 | - | | | | | | | | | | |
| 4. CompSize | 1-3 | 2.62 | .66 | .003 | .021 | -.080 | - | | | | | | | | | |
| 5. Familiarity | 1-10 | 6.89 | 1.82 | .049 | .013 | -.023 | .112 | - | | | | | | | | |
| 6. Technical Skill | 1-10 | 6.59 | 1.58 | .176* | .052 | -.069 | .057 | .294** | - | | | | | | | |
| 7. Social Skill | 1-9 | 4.28 | 1.99 | .133 | .030 | -.175* | .174* | .057 | .587** | - | | | | | | |
| 8. Intuitive Ability | 1-10 | 6.10 | 2.73 | .216** | .037 | -.065 | .256** | .130 | .489** | .463** | - | | | | | |
| 9. Learning | 1-10 | 6.42 | 2.26 | .176* | -.029 | -.067 | .181* | .187* | .625** | .547** | .348** | - | | | | |
| 10. Autocorrec Skills | 1-10 | 7.24 | 2.21 | .068 | .038 | -.122 | .125 | .222** | .354** | .231** | .367** | .276** | - | | | |
| 11. Drive | 1-10 | 5.29 | 2.45 | .047 | .034 | -.072 | -.217** | .083 | .100 | .171* | -.013 | .027 | .047 | - | | |
| 12. GlobalSubst | 1-10 | 6.33 | 1.60 | .167* | -.065 | .009 | .031 | .220** | .341** | .335** | .304** | .237** | .193* | .023 | - | |
| 13. Trust | 2-10 | 6.86 | 1.75 | .061 | .020 | -.048 | .171* | .323** | .412** | .343** | .351** | .348** | .268** | .140 | .265** | - |
| 14. Attitude_AI | 0-10 | 6.65 | 2.00 | .033 | -.001 | -.037 | .155* | .360** | .353** | .332** | .275** | .290** | .287** | .152* | .397** | .484** |

*p<.05, **p<.01

Outside the skills set, trust in benevolent AI effects has the highest mean (6.86) followed by attitudes towards investing in AI for e-HRM and a-HRM (6.65) and global job substitutability (6.33). All fell in the positive side of the scale.

Sociodemographic variables scarcely correlate with the main constructs under analysis. Gender does correlate with age, thus suggesting that participant males in our sample tend to be older but this does not affect directly our research model, only its possible generalizability. Overall males tend to perceive tech, intuitive, learning skills are more easily replaceable by AI than female. On the other hand, age has no significant correlation with any variable under study which suggests findings are not specific of any age group. Company size only has minor positive correlations with some variables to the exception of "drive" which shows a negative correlation ($r=-.217$, $p<.01$). Likewise, to the exception of a negative correlation between education and social skills replaceability (more educated individuals tend to perceive social skills as less replaceable by AI), education also shows no other case of significant correlation.

A variable of interest concerns familiarity with AI. This variable does present its positive significant correlations with overall attitude towards AI ($r=.360$, $p<.01$), trust ($r=.323$, $p<.01$), technical skills ($r=.294$, $p<.01$), autocorrection skills ($r=.222$, $p<.01$), global substitutability ($r=.220$, $p<.01$), and learning ($r=.187$, $p<.05$). This suggests that familiarity is a variable one should take into consideration.

Considering the correlations within skills, it is apparent that all are positively intercorrelated as expectable in a construct that shares a common subject "that of competency" while the item "drive" strikingly contrasts by the almost absent significant correlations. To the exception of "social skills" ($r=.171$, $p<.05$) it is void of any significant correlation which encourages our ex-ante judgment that it falls into a different category than that of skill.

As regards the correlation between skills and the main variables in the model, skills do show a positive significant correlation with all key variables, namely, trust, global substitutability, and attitude towards AI. Repeating the pattern, drive does fail to do so. Lastly, the variables involved in the moderation section of the model are also positively correlated. This scenario is very encouraging regarding the hypothesized model.

## 5.2. Hypothesis testing

In order to test Hypothesis 1, we used SPSS 25, applying PROCESS macro (model 4) (Hayes, 2017). We have requested bootstrapped estimates from 5,000 samples to construct bias-corrected confidence intervals. This first Hypothesis predicted that overall job substitution perception by machine and AI mediated the positive relationship between perceived workers 'skill replaceability and attitude towards AI in e-HRM and a-HRM.

Following the results of the factorial analysis, we conducted six different tests for each of the construct extracted, namely: 1. Technical Skills; 2. Social Skills; 3. Intuitive ability; 4. Learning Capacity; 5. Autocorrection skills; 6. Drive.

For each of the following analysis, we have also included individual demographic characteristics, because they can affect the relationship of interest. We have added gender, education, company size, and familiarity with AI, IT employee and HR employee as control variables, however, in all cases only familiarity controls shown to be significantly related to our variables.

## 5.3. Hypothesis 1

*Hypothesis 1: Techskill → globalReplaceability → Attitude*

Findings show the path between perceived technical skills replaceability, perceived overall job substitution and attitude towards AI was positive and significant (appendix B1). In addition, the 95% confidence intervals for this relationship did not contain zero. However, the direct effect between perceived technical skills replaceability and attitude towards AI was significant, partially, rather than full. The partially mediated indirect effect was .10 and the 95% confidence interval (.03, .20) did not include zero, offering support for Hypothesis 1.

*Hypothesis 1: SocialSkills → globalReplaceability → Attitude*

The path between perceived social skills replaceability, perceived overall job substitution and attitude towards AI was positive and significant (appendix B2). In addition, the 95% confidence intervals for this relationship did not contain zero. However, the direct effect between perceived social skills replaceability and attitude towards AI was significant, partially, rather than full. The partially mediated indirect effect was .09 and the 95% confidence interval (.02, .19) did not include zero, offering support for Hypothesis 1.

*Hypothesis 1: Intuitive_ability → globalReplaceability → Attitude*

The path between perceived intuitive ability replaceability, perceived overall job substitution and attitude towards AI was positive and significant (appendix B3). In addition, the 95% confidence intervals for this relationship did not contain zero. However, given that the direct effect between perceived intuitive ability replaceability and attitude towards AI was significant, partially, rather than full. The partially mediated indirect effect was .06 and the 95% confidence interval (.02, .12) did not include zero, offering support for Hypothesis 1.

*Hypothesis 1: Learning_capacity → globalReplaceability → Attitude*

The path between perceived learning capacity replaceability, perceived overall job substitution and attitude towards AI contains no mediation (appendix B4). In addition, the 95% confidence intervals for this relationship did contain zero. The mediated indirect effect was .04 and the 95% confidence interval (-.01, .12) did include zero, not supporting Hypothesis 1.

*Hypothesis 1: Autocorrection → globalReplaceability → Attitude*

The path between autocorrection skill replaceability, perceived overall job substitution and attitude towards AI contains no mediation (appendix B5). In addition, the 95% confidence intervals for this relationship did contain zero. The mediated indirect effect was .04 and the 95% confidence interval (-.01, .11) did include zero, not supporting Hypothesis 1.

*Hypothesis 1: Drive → globalReplaceability → Attitude*

The Drive's behavior contrasts with all other variables seen before. Total effect of drive on attitude towards AI was not significant as the 95% confidence interval (-.05, .19) did cross zero (appendix B6). Similarly, the direct effect was also not significant, as the 95% confidence interval (-.05, .17) crossed zero. The path between Drive, perceived overall job substitution and attitude towards AI contains no mediation. The mediated indirect effect was .01 and the 95% confidence interval (-.04, .06) did include zero, not supporting Hypothesis 1.

## 5.4.Hypothesis 2

To test Hypothesis 2, we have applied PROCESS macro (model 14) (Hayes, 2017). We have requested bootstrapped estimates from 5,000 samples to construct bias-corrected confidence intervals. This second Hypothesis predicted that the indirect effect between perceived skills replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception, will vary by the level of Trust and that this indirect effect will be stronger when Trust is high.

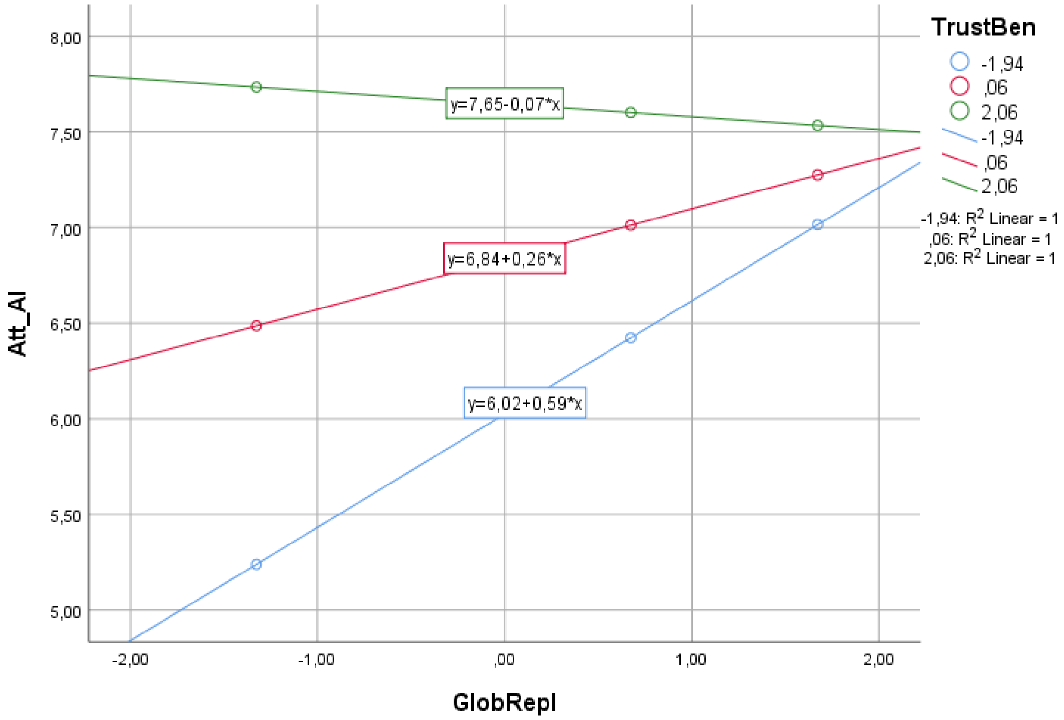
Following the results of the factorial analysis, we conducted again six tests for each of the construct extracted before, namely: 1. Technical Skills; 2. Social Skills; 3. Intuitive ability; 4. Learning Capacity; 5. Autocorrection skills; 6. Drive.

For each of the following analysis, we have also controlled for individual demographic characteristics, taken as covariates, because they can affect the relationship of interest. We have added gender, education, company size, familiarity with AI, IT employee and HR employee as control variables, however, in all cases only familiarity controls shown to be a significant predictor (appendices C).

*Hypothesis 2: Techical skills→GlobalSubstit→Att_AI (Ttrust as moderator in step 2)*

Results support this hypothesis, as the indirect effect when trust was high was .08 and the 95% confidence interval (.02, .15) did not contain zero (appendix C1, Graph 5.2). When trust was low, the indirect effect was .16 and the 95% confidence interval (-.06, -.30) also did not contain zero. For a really high level of trust, the moderator effect of trust is not significant, since the 95% confidence interval (-.09, .06) contained zero. Finally, the index for moderated mediation (Hayes, 2015) was -.04, and the 95% confidence interval (-.09, -.01) did not contain zero. Together these results support the Hypothesis 2, given that the indirect effect between perceived technical skills replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is dependent on trust.

*Graph 5.2 – Trust Moderator in Global Replaceability – Attitude*




*Hypothesis 2: Social skills->GlobalSubstit->Att_AI (trust as moderator in step 2)*

Results support this hypothesis, as the indirect effect when trust was high was .06 and the 95% confidence interval (.02, .14) did not contain zero (appendix C2). When trust was low, the indirect effect was .15 and the 95% confidence interval (.06, .27) did not contain zero. For really high level of trust, the moderator effect of trust is not significant, since the indirect effect was -.02 and the 95% confidence interval (-.09, .05) contained zero. Finally, the index of moderator mediation (Hayes, 2015) was -.04, and the 95% confidence interval (-.08, -.01) did not contain zero. Together these results support the Hypothesis 2, given that the indirect effect between perceived social skills replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is dependent on trust. The moderation effect graph is not depicted for parsimony sake, as it is identical to Graph 5.2.

*Hypothesis 2: Intuitive->GlobalSubstit->Att_AI (trust as moderator in step 2)*

The indirect effect when trust was high was .04 and the 95% confidence interval (.01, .09) did not contain zero (Appendix C3). When trust was low, the indirect effect was .09 and the 95% confidence interval (.03, .17) did not contain 0. For really high level of trust, the moderator effect of trust is not significant, since the indirect effect was -.00 and the 95% confidence interval (-.05, .04) contained zero. Finally, the index of moderator mediation (Hayes, 2015) was -.02, and the 95% confidence interval (-.05, -.01) did not contain zero. Together these results support the Hypothesis 2, given that the indirect effect between perceived intuitive ability replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is dependent on trust. For the effect graph please refer to Graph 5.2.

*Hypothesis 2: Learning->GlobalSubstit->Att_AI (trust as moderator in step 2)*

The indirect effect when trust was high was .03 and the 95% confidence interval (-.01, .09) did contain zero (appendix C4). When trust was low, the indirect effect was .07 and the 95% confidence interval (-.01, .17) did contain 0. For really high level of trust also, the moderator effect of trust is not significant, since the indirect effect was -.00 and the 95% confidence interval (-.04, .03) contained zero. Finally, the index of moderated mediation (Hayes, 2015) was -.02, and the 95% confidence interval (-.04, .00) did contain zero. Together these results do not support the Hypothesis 2, given that the indirect effect between perceived learning capacity replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is not dependent on trust.

*Hypothesis 2: Autocorrection->GlobalSubstit->Att_AI (trust as moderator in step 2)*

The indirect effect when trust was high was .03 and the 95% confidence interval (-.01, .08) did contain zero (appendix C5). When trust was low, the indirect effect was .06 and the 95% confidence interval (-.01, .14) did contain zero. For really high level of trust also, the moderator effect of trust is not significant, since the indirect effect was -.00 and the 95% confidence interval (-.03, .03) contained zero. Finally, the index of moderator mediation (Hayes A. F., 2015) was -.01, and the 95% confidence interval (-.04, .00) did contain zero. Together these results do not support the Hypothesis 2, given that the indirect effect between perceived autocorrection skills replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is not dependent on trust

*Hypothesis 2: Drive->GlobalSubstit->Att_AI (trust as moderator in step 2)*

The indirect effect when trust was high was .00 and the 95% confidence interval (-.03, .04) did contain zero. When trust was low, the indirect effect was .01 and the 95% confidence interval (-.07, .08) did contain zero (appendix C6). For really high level of trust also, the moderator effect of trust is not significant, since the indirect effect was -.00 and the 95% confidence interval (-.01, .02) contained zero. Finally, the index of moderator mediation (Hayes, 2015) was -.00, and the 95% confidence interval (-.02, .02) did contain zero. Together these results do not support the Hypothesis 2, given that the indirect effect between drive replaceability and attitude towards AI in e-HRM and a-HRM, trough overall job substitution perception is not dependent on trust.

Overall, results offer a varying level of support to hypotheses as showed in Table 6.1.

*Table 6.1 Effects summary table*

| Variable | Total Effect | Direct Effect | (*H1*) Ind. Effect | (*H2*) Moderator Effect (*Trust*) |
|---|---|---|---|---|
| Tech. Skills | .37* | .27* | .10* | .16* (l)<br>.07* (m)<br>-.01 (h) |
| Social Skills | .28* | .19* | .09* | .14* (l)<br>.06* (m)<br>-.02 (h) |
| Intuitive Ability | .14* | .08* | .06* | .09* (l)<br>.04* (m)<br>-.00 (h) |
| Learning Capacity | .15* | .11 | .04 | .06 (l)<br>.03 (m)<br>-.00 (h) |
| Autocorrect. Skills | .22* | .18* | .03 | .06 (l)<br>.03 (m)<br>-.00 (h) |
| Drive | .07 | .06 | .01 | .01 (l)<br>.00 (m)<br>-.0 (h) |

* Significance; H2 column represents the three moderator effects for low, medium and high levels of trust.

# 6. Discussion and conclusion

## 6.1.Discussion of results

Our results confirm the model previously represented (*Fig. 3.1*), as we found significance for the main constructs under analysis. This result is congruent with conclusions proposed for HRIS implementation by Maier et al. (2012).

Concerning Hypothesis 1, findings show that technical skills, social skills and intuitive ability, do have a positive mediated relationship trough perceive overall job substitution with attitudes towards AI. Surprisingly, findings suggested that when these competences are perceived to be highly substitutable by intelligent technologies, people manifest a stronger positive attitude towards implementing AI.

This mediated relationship was not found neither for learning capacity nor for autocorrection skills. Additionally, for learning capacity the direct relationship to attitude towards AI was not significant.  Drive's behavior contrasted with all other variables, since we found neither a total effect, nor a direct relationship or indirect relationship.

Concerning Hypothesis 2, findings supported again the theoretical model for technical skills, social skills, and intuitive ability. On the contrary, we found no significance for learning capacity, autocorrection skill, and drive, supporting previous researches on role of trust in new technologies acceptance (e.g. Hengstler et al., 2015; Siau & Wang, 2018; Xin et al., 2008).

Having an overview of the results of our two hypotheses test we conclude that the perception of one's own skills replaceability is directly and positively associated to a favorable attitude towards AI in a-HRM for all constructs except learning capacity and drive. This means that when people are thinking on the possibility of substitution for these two elements, they are not consistently relating it (learning capacity and drive) with any consequence stemming from accepting AI technologies. Moreover, as expected, drive is not empirically related to our model and therefore our choice for this variable as a marker was proven to be suitable as a recommended strategy to account for CMV (Lindell and Whitney, 2001).

The indirect effects were confirmed for the first three competences: technical skills, social skills and intuitive ability. This means that in these cases the relationship between skills replaceability and positive attitude towards AI in HRM is mediated by overall perceived job substitution.

Finally, we observed that when this mediated relationship exists, the variable trust (the one with the highest mean outside the skills set) acts as a moderator, increasing the positive effects of skills replaceability perception on attitude. However, when trust in benevolent effects of AI is very high, its moderator role stops to produce significant effects on the relationship. It is logical to infer that when trust is very high, attitude towards AI will not increase substantially for any higher variation.

Another finding lies in the answers regarding overall perceived substitution (*item nr. 17*): none of the respondents answered with lowest item of the scale 0 (this will not happen). This means that all participants expect at least a certain level of human work substitution in the future. Surprisingly, these expectations do not affect negatively workers attitude towards AI.

A variable of interest concerns familiarity with AI. The significant correlations of this variable with all our main constructs states that people which consider themselves to be familiar with concept of AI tend to perceive technical skills and meta skills as more substitutable by intelligent machines. Such numbers point out that people do recognize room of improvement in these competence areas, if those skills would be replaced by AI performance.

We did not observe the same correlation with social skills. This is an important finding, since independently from familiarity with AI technologies and without apparently know their possibilities, there is an aversion in admitting that machines are better in performing social tasks (in line with Greshko, 2018). Also, there is a general tendency in our answers (4.28) to consider social skills non-substitutable. This is the only construct under analysis (excluding of course sociodemographic variables), which has a mean below the midpoint (5). Moreover, none of the respondents in this cluster gave in any of the skills the maximum score of substitutability (10). Therefore, we can observe a pessimistic perspective regarding the possibility for intelligent machines to replace social human features.

If we correlate all these elements to trust, we notice that (excluding drive) trust has no effect in the relationship between autocorrection skills and learning capacity to attitude towards AI. Autocorrection skills are also perceived as the most easily to be replaced (mean 7.4), thus we can conclude that people notice some fallacy in their autocorrection capacity, in line with Kahneman's (2011) consideration on cognitive *system 1*, mentioned in the literature review. This awareness does not negatively impact on attitude towards AI, however it is interesting to notice that for these skills, trust look weakened compared to the other variables. Therefore, we can point out that highest investment in automation is expectable where systematic human errors are most common, but in the long-term lack of trust may not produce a positive attitude towards these changes.

## 6.2. Conclusions: strengths, limitations and future research

After briefly reviewing the main technological revolutions, we stated that humans are currently experiencing a second machine age (Brynjolfsson & McAfee, 2014). This period is characterized by the substitution of mental power by AI, as in the past happened for physical strength and steam engine. Notably, we are now observing an initial phase where AI will start being used to replace white collars high-skilled jobs (Cohn, 2013; Haenssle et al., 2018).

This possibility of interacting with new technologies, make us question a critical dimension of technological implementation: its acceptance by social agents. Namely, we were interested in understanding workers willingness to accept and cooperate with AI in future. This doubt shows up naturally since those changes are going for sure to have a striking impact on labor market and on overall working environment. Following these considerations, trough the present research we set ourselves the objective to define and explore the associations between human attitude toward AI in e-HRM and a-HRM.

This study provides crucial theoretical contribution on the literature on the relationship between perceived skills replaceability and attitude towards AI, since research in this area is scarce if not virtually inexpressive, which affects as well social impacts of automation based on workers' perspective.

Moreover, we deemed appropriate to formulate and introduce during our reasoning the new term *a-HRM*, which stands for *automated Human Resources Management*. In this way, we offer what we believe to be an updated conception of emerging HRM beyond the conceptual domain of the most commonly used concept of *e-HRM* (electronic Human Resources Management), by creating a new essential perspective for future investigation in HRM area.

What machines are currently achieving in HR (as well as in other areas) is not merely digitalization of task through IT, but to make complete roles automated. Thus, we coined this new term to indicate all processes in Human Resources Management which aim to automate (or improve automation) task/roles using new technologies, programs and AI tools. As the previous e-HRM, also a-HRM should be considered as an umbrella term (Bondarouk & Ruël, 2009), since these kind of processes aim to create value across the organization to all employees and they are not limited only to HR.

Roles automation may be perceived positively by workers in case those changes are beneficial, but the fact of losing "control" on some key roles in their working activity may also be an erosive factor acting on trust in intelligent machines. Starting from this assumption, we have been able to connect the workers' perception substitution (by machine and AI), trust and their attitude toward these new technologies. We have focused our attention on skills, and how these are perceived to be substituted by intelligent technologies.

Initially, we thought that the higher the perception of substitution, the higher the aversion to automation would be. It was logical for us to assume that the threat of a machine outperforming human work and therefore to have the potential to override it, would make people afraid of automation. Surprisingly, this is not the real situation: for high perception of substitution, workers still have a positive attitude toward AI implementation in a-HRM.

We can explain this trend trough the interpretation of the role that *trust* plays in our model. Trust acts as a moderator in the *substitution perception* and *attitude towards AI in a-HRM* relationship (*Fig.3.1*). This moderator role seems to be quite strong if we consider the percentage comparing the feeling of job substitution, which our sample expressed in their answers.

One important finding stands exactly in this area: none of the respondents affirmed that job replaceability will definitively not happen for much of human work. This means that everybody expects that in machines will in a certain measure replace human work, even though this does not represent a reason of being against those changes. Following considerations provided by cognitive psychology, this can be explained by psychological bias concerning bad things only happen to others (Kahneman, 2011).

It is possible to explain such consideration assuming that people in this moment are only looking to AI innovation as a possibility to improve their work and standard life conditions. In other words, people put their trust in machines' revolution.

This outcome is congruent with current situation. We have recently surpassed the emergent phase of *Narrow AI,* were intelligent machines are capable to perform only particular tasks in a well-defined situation. We started to go through a disruptive moment where we are handling *Broad AI* (technologies capable to perform wider complex task e.g. autonomous drive or project debater) (Ford, 2015; Lightstone, 2019). In about 30 years, It will be expectable to face a third phase, which many calls revolutionary: this last moment is characterized by the rise of *General AI* (something really similar to human intelligence) where machines will be able to perform multiple complex generalized tasks in real world scenario (Lightstone, 2019).

Our results state that opportunity of investments in AI are enormous and social impact for workers is positive. Therefore, we do not expect any side effect regarding employees' acceptance of such technologies. Accordingly, we do expect companies will adopt a-HRM policy pursing the path of techno enhancement trough AI. This trend will not be opposed by any social resistance and workers may willingly cooperate using and accepting AI tools.

This scenario will probably remain stable until AI strongly strikes labor market. At this point the dynamics could change and workers attitudes will have to be studied again as social or political movements can easily base their rising power upon general discontentment with AI impact.

Reasoning on future consequences, one critical issue could be found in *replaceability of social skills*. As seen before, our sample is not confident regarding the possibility of substitution for this set of skills. Their positive trust and attitude for sure depends on this assumption. So, what If engineering bottleneck respecting communication of social skills to machines is overtaken? What if AI evolves to the point of mimicking true social interactions with the indistinguishable feature of it being artificial?

For technical skills, we already assume machine to be better than humans, but we do not have the same feeling relatively the relational competences. In the future this may change and consequences on human attitudes towards machines should be probably recalculated.

In this perspective, it would be important to give continuity to researches of this kind, and analyze workers perception of substitutability by AI in a longer period, in order to be capable to monitor the phenomenon and predict its developments. It would also be important to restrain the domain of jobs in the sense of studying specific job families, e.g. physicians, teachers, financial analysts, etc.

One of the limits of this research it is indeed represented by carrying out the study in a short period of time (1 year), while it would be interesting to extend it and establish a temporal analysis, which could be a pointer for the magnitude of workers attitude implications in a-HRM facing AI technologies. Likewise, it would offer some insight about the stability of their positions and trend.

This would be valuable especially if we consider that automation will bring relevant mutations in human-machine frontier within existing task and will impose a new reskilling imperative: by 2022 it is expected that no less than 54% of all employees will require a significant up and reskilling (World Economic Forum, 2018).

Analytical thinking, active learning, creativity will be on the top of new skills demand (World Economic Forum, 2018), therefore, social and psychological impact on workers of these automation changes should not be underestimated.

Employees may not match the new skills demand. This could weaken their trust in AI and automation and therefore have a negative impact on their attitudes. This perspective needs to be further studied on a longer temporary horizon, since workers attitude face AI could be a key factor of the success of such investments.

Lastly, it could be also important to explore qualitatively some possible findings: since this study is limited to a quantitative analysis, it does not provide a deep assessment on individual perspective but an overall view of the phenomenon. However, in doing so, we expect to offer a contribute to the way future researches can deepen the concept of attitude towards AI based on substitution perception of one's own skills in a-HRM.

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# Appendix

## *Appendix A – Questionnaire*



# Automation in e-HRM: a job replacement focus

This survey integrates into a Master's thesis project, which main objective is to establish to what extent the e-HRM human skills are substitutable by machines and Artificial Intelligence. Our starting point is the workers' awareness of this phenomenon and the degree of confidence/mistrust they express about it.

The same is anonymous and strictly confidential. There are no right or correct answers, we are only interested in knowing your opinion.
It will take maximum 10 minutes to answer all questions.

Thanks for your collaboration!

*Required

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Instituto Universitário de Lisboa

### Skills replaceability by Machine and AI

### Please indicate for each of the skills below, how much in your opinion (from 1 to 10) these can be substituted by machine and Artificial Intelligence.

1. **Goal Setting: ability to filter and organize information to define one's own objectives.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | | | | | | | | | | | Fully replaceable by machine and AI |

2. **Integrity: performing honest and ethical behavior contextualized to specific work environment and situations.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | | | | | | | | | | | Fully replaceable by machine and AI |

3. **Problem Solving: capacity to handle situations and to solve problems in complex, real-world settings.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

4. **Resource Management Skills: capacity to allocate resources efficiently.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

5. **Social Skills: capacity used to work and interact with people to better achieve goals.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

6. **Technical Skills: capacity to design, set-up, operate and correct malfunctions, involving application of machines or technological systems.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

7. **System Skills: capacity to understand, monitor, and improve overall systems (this includes system analysis and evaluation).** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

8. **Autocorrection Skills: ability to identify and correct one's own systematic and unconscious errors.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Fully replaceable by machine and AI |

9. **Learning Capacity: ability to acquire knowledge to improve one's own work processes to enhance job performance.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

10. **Planning and Organizational Skills: capacity to control/delegate subordinates, organize resources to better achieve goals and to plan work activity accordingly.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

11. **Group Empowerment Skills: ability to enhance one's own work by interacting with others and improve jointly the quality of the group itself (e.g. Team or network of machines).** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

12. **Communication Skills: capacity to clearly communicate implicit and explicit messages.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

13. **Empathy: ability to understand the other's point of view in an accurate way.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

14. **Influencing others: ability to persuade others to do something they otherwise would not do.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

15. **Intuitive Ability: capacity to deduce complete patterns from partial information.** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Fully irreplaceable by machine and AI | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Fully replaceable by machine and AI |

16. **Finally; considering that a machine (computer, robot etc.) will endure 100% level of energy in the full period of activity. Comparing human drive (energy, initiative, job motivation, tenacity, work standard perception, fatigue) with machines, how much would you estimate that human drive can match machine performance?** *
*Mark only one oval.*

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Humans cannot match machines performance (0%) | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Human fully match machines performance (100%) |

## Trust in Machine and AI

17. **Do you think that much of the work currently done by humans will in future be substituted by machines?** *
*Mark only one oval.*

- ⬭ This will definitively happen
- ⬭ This will probably happen
- ⬭ This will probably not happen
- ⬭ This will definitively not happen

18. **Only if you answer positively to the previous question. Could you please estimate the percentage 0% to 100%) of this replacement magnitude?**
*Mark only one oval.*

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Almost none of human works will be replaced by machines (0%) | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | Almost all human works will be replaced by machines (100%) |

19. **How much do you trust the investments in automation through machines and AI, as a measure to help workers in their daily activities?** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| I totally don't trust | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | I totally trust |

20. **If you were a decision maker in a big company…From 0% to 100%, how would you think should your company invest putting AI inside HRM making it automated, electronic and digitalized?** *
*Mark only one oval.*

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (0%) I wouldn't implement this kind of investments | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | (100%) I would be totally in favor of this kind of investments |

## Personal information

21. **Age** *

22. **Education (field of study and educational level)** *

23. **Gender** *
*Mark only one oval.*
- M
- F

24. **Current function** *

25. **If you are currently working, could you please indicate the size of your company?**
*Mark only one oval.*
- Small
- Medium
- Large

26. **How much are you familiar with the concept of AI (Artificial Intelligence)?** *
*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| I have no idea of what AI is | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | ⬭ | I'm fully aware of the new technologies and possibilities |

## *Appendix B1 - Techskill → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : TechSkil
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3707      ,1374     2,3207     3,4829     7,0000   153,0000      ,0017

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,1614     1,0533     3,0013      ,0031     1,0804     5,2423
TechSkil      ,2810      ,0845     3,3254      ,0011      ,1141      ,4479
Gender        ,1945      ,2550      ,7628      ,4468     -,3092      ,6982
Educatio      ,0514      ,2135      ,2406      ,8102     -,3703      ,4731
CompSize      ,0683      ,1877      ,3640      ,7164     -,3025      ,4392
Familiar      ,1240      ,0718     1,7269      ,0862     -,0179      ,2659
IT            ,0760      ,3462      ,2195      ,8265     -,6079      ,7599
HR           -,4484      ,2828    -1,5857      ,1149    -1,0070      ,1102

Standardized coefficients
              coeff
TechSkil      ,2629
Gender        ,0608
Educatio      ,0183
CompSize      ,0281
Familiar      ,1358
IT            ,0178
HR           -,1351

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5513      ,3040     2,7680     8,2974     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,5036     1,1838      ,4255      ,6711    -1,8351     2,8424
TechSkil      ,2693      ,0956     2,8180      ,0055      ,0805      ,4581
GlobRepl      ,3697      ,0883     4,1875      ,0000      ,1953      ,5442
Gender       -,2929      ,2790    -1,0499      ,2954     -,8442      ,2583
Educatio     -,0245      ,2332     -,1053      ,9163     -,4852      ,4361
CompSize      ,1931      ,2051      ,9412      ,3481     -,2122      ,5983
Familiar      ,2799      ,0792     3,5354      ,0005      ,1235      ,4364
IT            ,3327      ,3781      ,8798      ,3804     -,4144     1,0797
HR           -,0099      ,3113     -,0318      ,9747     -,6250      ,6052

Standardized coefficients
              coeff
TechSkil      ,2079
GlobRepl      ,3051
```

```
Gender       -,0756
Educatio     -,0072
CompSize      ,0654
Familiar      ,2531
IT            ,0641
HR           -,0025

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4729      ,2237     3,0671     6,2972     7,0000   153,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,6725     1,2110     1,3811      ,1693     -,7199     4,0648
TechSkil      ,3732      ,0971     3,8416      ,0002      ,1813      ,5651
Gender       -,2210      ,2931     -,7540      ,4520     -,8001      ,3581
Educatio     -,0056      ,2454     -,0226      ,9820     -,4904      ,4793
CompSize      ,2183      ,2158     1,0116      ,3133     -,2080      ,6447
Familiar      ,3258      ,0826     3,9465      ,0001      ,1627      ,4889
IT            ,3608      ,3980      ,9065      ,3661     -,4255     1,1470
HR           -,1757      ,3251     -,5404      ,5897     -,8179      ,4665

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps       c_cs
      ,3732      ,0971     3,8416      ,0002      ,1813      ,5651      ,1920      ,2881

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps      c'_cs
      ,2693      ,0956     2,8180      ,0055      ,0805      ,4581      ,1385      ,2079

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,1039      ,0483      ,0285      ,2167

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0534      ,0235      ,0153      ,1071

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0802      ,0356      ,0226      ,1615

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

## *Appendix B2 - SocialSkills → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : SocSkill
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4032      ,1626     2,2530     4,2443     7,0000   153,0000      ,0003

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,4583      ,9994     3,4603      ,0007     1,4838     5,4327
SocSkill      ,2533      ,0633     3,9984      ,0001      ,1281      ,3784
Gender        ,2920      ,2482     1,1767      ,2412     -,1983      ,7824
Educatio      ,1755      ,2122      ,8273      ,4094     -,2437      ,5948
CompSize     -,0377      ,1875     -,2008      ,8411     -,4081      ,3328
Familiar      ,1604      ,0688     2,3307      ,0211      ,0244      ,2963
IT           -,0567      ,3434     -,1653      ,8690     -,7351      ,6216
HR           -,2173      ,2887     -,7526      ,4528     -,7877      ,3531

Standardized coefficients
              coeff
SocSkill      ,3176
Gender        ,0913
Educatio      ,0625
CompSize     -,0155
Familiar      ,1757
IT           -,0133
HR           -,0655

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5452      ,2973     2,7946     8,0375     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,0148     1,1558      ,8780      ,3813    -1,2688     3,2983
SocSkill      ,1878      ,0741     2,5334      ,0123      ,0413      ,3343
GlobRepl      ,3642      ,0900     4,0445      ,0001      ,1863      ,5421
Gender       -,1894      ,2777     -,6822      ,4961     -,7380      ,3592
Educatio      ,0703      ,2369      ,2966      ,7672     -,3977      ,5382
CompSize      ,1190      ,2088      ,5697      ,5698     -,2936      ,5316
Familiar      ,3206      ,0780     4,1114      ,0001      ,1666      ,4747
IT            ,2410      ,3825      ,6301      ,5296     -,5146      ,9966
HR            ,1388      ,3222      ,4310      ,6671     -,4977      ,7754

Standardized coefficients
              coeff
SocSkill      ,1944
```

| | |
|---|---|
| GlobRepl | ,3005 |
| Gender | -,0489 |
| Educatio | ,0206 |
| CompSize | ,0403 |
| Familiar | ,2899 |
| IT | ,0465 |
| HR | ,0345 |

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

Att_AI

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| ,4708 | ,2216 | 3,0751 | 6,2242 | 7,0000 | 153,0000 | ,0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 2,2742 | 1,1676 | 1,9477 | ,0533 | -,0326 | 4,5809 |
| SocSkill | ,2800 | ,0740 | 3,7845 | ,0002 | ,1339 | ,4262 |
| Gender | -,0831 | ,2900 | -,2865 | ,7749 | -,6559 | ,4898 |
| Educatio | ,1342 | ,2479 | ,5413 | ,5891 | -,3556 | ,6240 |
| CompSize | ,1053 | ,2191 | ,4805 | ,6315 | -,3275 | ,5380 |
| Familiar | ,3790 | ,0804 | 4,7148 | ,0000 | ,2202 | ,5379 |
| IT | ,2203 | ,4012 | ,5492 | ,5837 | -,5722 | 1,0128 |
| HR | ,0597 | ,3373 | ,1770 | ,8597 | -,6067 | ,7261 |

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

| Effect | se | t | p | LLCI | ULCI | c_ps | c_cs |
|---|---|---|---|---|---|---|---|
| ,2800 | ,0740 | 3,7845 | ,0002 | ,1339 | ,4262 | ,1441 | ,2898 |

Direct effect of X on Y

| Effect | se | t | p | LLCI | ULCI | c'_ps | c'_cs |
|---|---|---|---|---|---|---|---|
| ,1878 | ,0741 | 2,5334 | ,0123 | ,0413 | ,3343 | ,0966 | ,1944 |

Indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0922 | ,0430 | ,0259 | ,1921 |

Partially standardized indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0474 | ,0213 | ,0139 | ,0970 |

Completely standardized indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0955 | ,0428 | ,0284 | ,1936 |

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

NOTE: Variables names longer than eight characters can produce incorrect output.
Shorter variable names are recommended.

------ END MATRIX ----

*Appendix B3 - Intuitive_ability → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : Intuitio
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3651      ,1333     2,3319     3,3608     7,0000   153,0000      ,0023

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,2334      ,9899     4,2766      ,0000     2,2778     6,1891
Intuitio      ,1515      ,0473     3,2043      ,0016      ,0581      ,2449
Gender        ,1648      ,2575      ,6399      ,5232     -,3440      ,6736
Educatio      ,0486      ,2140      ,2272      ,8206     -,3742      ,4714
CompSize     -,0607      ,1937     -,3133      ,7545     -,4433      ,3219
Familiar      ,1610      ,0701     2,2968      ,0230      ,0225      ,2995
IT            ,0802      ,3470      ,2311      ,8176     -,6053      ,7657
HR           -,4525      ,2834    -1,5965      ,1125    -1,0124      ,1075

Standardized coefficients
              coeff
Intuitio      ,2573
Gender        ,0515
Educatio      ,0173
CompSize     -,0249
Familiar      ,1764
IT            ,0187
HR           -,1363

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5277      ,2785     2,8692     7,3343     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,4627     1,1618     1,2590      ,2100     -,8327     3,7581
Intuitio      ,0821      ,0542     1,5158      ,1316     -,0249      ,1892
GlobRepl      ,4002      ,0897     4,4631      ,0000      ,2231      ,5774
Gender       -,2628      ,2860     -,9187      ,3597     -,8279      ,3024
Educatio     -,0234      ,2374     -,0985      ,9216     -,4924      ,4457
CompSize      ,1282      ,2149      ,5967      ,5516     -,2963      ,5528
Familiar      ,3188      ,0791     4,0311      ,0001      ,1626      ,4751
IT            ,3436      ,3850      ,8925      ,3735     -,4170     1,1042
HR           -,0333      ,3170     -,1052      ,9164     -,6596      ,5929

Standardized coefficients
              coeff
Intuitio      ,1151
```

```
GlobRepl      ,3303
Gender       -,0678
Educatio     -,0069
CompSize      ,0434
Familiar      ,2882
IT            ,0663
HR           -,0083

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4289      ,1840     3,2240     4,9272     7,0000   153,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,1571     1,1640     2,7124      ,0074      ,8576     5,4566
Intuitio      ,1428      ,0556     2,5679      ,0112      ,0329      ,2526
Gender       -,1968      ,3028     -,6500      ,5167     -,7950      ,4014
Educatio     -,0039      ,2516     -,0157      ,9875     -,5010      ,4932
CompSize      ,1039      ,2277      ,4564      ,6487     -,3459      ,5538
Familiar      ,3833      ,0824     4,6497      ,0000      ,2204      ,5461
IT            ,3757      ,4080      ,9208      ,3586     -,4304     1,1817
HR           -,2144      ,3332     -,6435      ,5209     -,8728      ,4439




************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps       c_cs
      ,1428      ,0556     2,5679      ,0112      ,0329      ,2526      ,0735      ,2001

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps      c'_cs
      ,0821      ,0542     1,5158      ,1316     -,0249      ,1892      ,0423      ,1151

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0606      ,0272      ,0173      ,1231

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0312      ,0133      ,0093      ,0616

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0850      ,0364      ,0247      ,1659

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix B4 Learning_capacity → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : Learning
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3050      ,0931     2,4401     2,2426     7,0000   153,0000      ,0337

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,0653     1,0285     3,9525      ,0001     2,0333     6,0973
Learning      ,1055      ,0606     1,7400      ,0839     -,0143      ,2253
Gender        ,2718      ,2603     1,0443      ,2980     -,2424      ,7860
Educatio      ,0570      ,2189      ,2605      ,7948     -,3754      ,4894
CompSize      ,0386      ,1944      ,1983      ,8431     -,3455      ,4226
Familiar      ,1580      ,0728     2,1719      ,0314      ,0143      ,3018
IT            ,0585      ,3558      ,1645      ,8696     -,6445      ,7615
HR           -,4239      ,2961    -1,4318      ,1542    -1,0088      ,1610

Standardized coefficients
              coeff
Learning      ,1432
Gender        ,0850
Educatio      ,0203
CompSize      ,0158
Familiar      ,1731
IT            ,0137
HR           -,1277

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5299      ,2808     2,8600     7,4189     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,1458     1,1690      ,9802      ,3286    -1,1638     3,4554
Learning      ,1108      ,0663     1,6714      ,0967     -,0202      ,2418
GlobRepl      ,4139      ,0875     4,7294      ,0000      ,2410      ,5869
Gender       -,2388      ,2828     -,8444      ,3998     -,7974      ,3199
Educatio     -,0224      ,2370     -,0944      ,9249     -,4906      ,4459
CompSize      ,1562      ,2105      ,7422      ,4591     -,2597      ,5721
Familiar      ,3022      ,0800     3,7788      ,0002      ,1442      ,4602
IT            ,3071      ,3853      ,7970      ,4267     -,4541     1,0683
HR            ,0479      ,3227      ,1485      ,8821     -,5896      ,6854

Standardized coefficients
              coeff
Learning      ,1241
GlobRepl      ,3416
Gender       -,0616
```

| | |
|---|---|
| Educatio | -,0066 |
| CompSize | ,0529 |
| Familiar | ,2732 |
| IT | ,0592 |
| HR | ,0119 |

************************** TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:
Att_AI

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| ,4183 | ,1750 | 3,2595 | 4,6359 | 7,0000 | 153,0000 | ,0001 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 2,8287 | 1,1888 | 2,3795 | ,0186 | ,4802 | 5,1772 |
| Learning | ,1545 | ,0701 | 2,2042 | ,0290 | ,0160 | ,2930 |
| Gender | -,1263 | ,3008 | -,4198 | ,6752 | -,7205 | ,4680 |
| Educatio | ,0012 | ,2530 | ,0049 | ,9961 | -,4985 | ,5010 |
| CompSize | ,1722 | ,2247 | ,7663 | ,4447 | -,2717 | ,6161 |
| Familiar | ,3676 | ,0841 | 4,3718 | ,0000 | ,2015 | ,5338 |
| IT | ,3313 | ,4113 | ,8055 | ,4218 | -,4812 | 1,1438 |
| HR | -,1275 | ,3422 | -,3727 | ,7099 | -,8035 | ,5485 |

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

| Effect | se | t | p | LLCI | ULCI | c_ps | c_cs |
|---|---|---|---|---|---|---|---|
| ,1545 | ,0701 | 2,2042 | ,0290 | ,0160 | ,2930 | ,0795 | ,1730 |

Direct effect of X on Y

| Effect | se | t | p | LLCI | ULCI | c'_ps | c'_cs |
|---|---|---|---|---|---|---|---|
| ,1108 | ,0663 | 1,6714 | ,0967 | -,0202 | ,2418 | ,0570 | ,1241 |

Indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0437 | ,0332 | -,0077 | ,1226 |

Partially standardized indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0225 | ,0166 | -,0041 | ,0608 |

Completely standardized indirect effect(s) of X on Y:

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| GlobRepl | ,0489 | ,0357 | -,0089 | ,1313 |

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

NOTE: Variables names longer than eight characters can produce incorrect output.
Shorter variable names are recommended.

------ END MATRIX -----

## *Appendix B5 Autocorrection → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : Autocorr
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3033      ,0920     2,4430     2,2142     7,0000   153,0000      ,0360

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,8274     1,0657     3,5914      ,0004     1,7220     5,9328
Autocorr      ,0995      ,0590     1,6865      ,0937     -,0171      ,2160
Gender        ,3085      ,2586     1,1932      ,2346     -,2023      ,8194
Educatio      ,0883      ,2195      ,4024      ,6880     -,3454      ,5220
CompSize      ,0467      ,1940      ,2408      ,8100     -,3365      ,4300
Familiar      ,1668      ,0720     2,3164      ,0219      ,0245      ,3091
IT            ,1423      ,3558      ,3999      ,6898     -,5606      ,8451
HR           -,5122      ,2892    -1,7713      ,0785    -1,0836      ,0591

Standardized coefficients
              coeff
Autocorr      ,1334
Gender        ,0965
Educatio      ,0315
CompSize      ,0192
Familiar      ,1828
IT            ,0332
HR           -,1544

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5528      ,3055     2,7617     8,3597     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,5118     1,1799      ,4338      ,6651    -1,8193     2,8429
Autocorr      ,1824      ,0633     2,8820      ,0045      ,0574      ,3075
GlobRepl      ,4009      ,0860     4,6635      ,0000      ,2310      ,5707
Gender       -,2125      ,2762     -,7695      ,4428     -,7582      ,3331
Educatio      ,0318      ,2335      ,1360      ,8920     -,4296      ,4932
CompSize      ,1344      ,2063      ,6517      ,5156     -,2732      ,5420
Familiar      ,3015      ,0779     3,8700      ,0002      ,1476      ,4555
IT            ,4260      ,3785     1,1255      ,2621     -,3218     1,1737
HR           -,0310      ,3106     -,0999      ,9205     -,6447      ,5827

Standardized coefficients
              coeff
Autocorr      ,2019
GlobRepl      ,3308
Gender       -,0548
```

```
Educatio      ,0093
CompSize      ,0455
Familiar      ,2726
IT            ,0821
HR           -,0077

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4541      ,2062     3,1362     5,6772     7,0000   153,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,0461     1,2075     1,6945      ,0922     -,3395     4,4316
Autocorr      ,2223      ,0668     3,3262      ,0011      ,0903      ,3543
Gender       -,0889      ,2930     -,3033      ,7621     -,6676      ,4899
Educatio      ,0672      ,2487      ,2700      ,7875     -,4242      ,5586
CompSize      ,1532      ,2198      ,6968      ,4870     -,2811      ,5874
Familiar      ,3684      ,0816     4,5142      ,0000      ,2072      ,5296
IT            ,4830      ,4031     1,1982      ,2327     -,3134     1,2794
HR           -,2364      ,3277     -,7214      ,4718     -,8837      ,4110

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps       c_cs
      ,2223      ,0668     3,3262      ,0011      ,0903      ,3543      ,1144      ,2460

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps      c'_cs
      ,1824      ,0633     2,8820      ,0045      ,0574      ,3075      ,0938      ,2019

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0399      ,0292     -,0086      ,1062

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0205      ,0145     -,0047      ,0531

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0441      ,0309     -,0103      ,1123

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.
------ END MATRIX -----
```

## *Appendix B6 Drive → globalReplaceability → Attitude*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Att_AI
    X  : Drive
    M  : GlobRepl

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2753      ,0758     2,4865     1,7931     7,0000   153,0000      ,0924

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,2604     1,0898     3,9094      ,0001     2,1074     6,4134
Drive         ,0183      ,0535      ,3427      ,7323     -,0874      ,1240
Gender        ,3265      ,2607     1,2523      ,2124     -,1886      ,8416
Educatio      ,0686      ,2217      ,3095      ,7573     -,3694      ,5066
CompSize      ,1028      ,1997      ,5146      ,6075     -,2917      ,4972
Familiar      ,1801      ,0724     2,4858      ,0140      ,0370      ,3232
IT            ,1122      ,3589      ,3126      ,7550     -,5969      ,8213
HR           -,5377      ,2913    -1,8457      ,0669    -1,1133      ,0378

Standardized coefficients
              coeff
Drive         ,0277
Gender        ,1021
Educatio      ,0244
CompSize      ,0422
Familiar      ,1972
IT            ,0262
HR           -,1620

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5228      ,2734     2,8897     7,1480     8,0000   152,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,9585     1,2321      ,7779      ,4378    -1,4758     3,3928
Drive         ,0634      ,0577     1,0984      ,2738     -,0506      ,1774
GlobRepl      ,4317      ,0872     4,9530      ,0000      ,2595      ,6039
Gender       -,1951      ,2825     -,6905      ,4909     -,7532      ,3631
Educatio      ,0040      ,2391      ,0167      ,9867     -,4683      ,4763
CompSize      ,2602      ,2154     1,2080      ,2289     -,1654      ,6858
Familiar      ,3160      ,0796     3,9674      ,0001      ,1586      ,4734
IT            ,3802      ,3871      ,9822      ,3276     -,3846     1,1449
HR           -,0594      ,3176     -,1870      ,8519     -,6868      ,5680

Standardized coefficients
              coeff
Drive         ,0790
GlobRepl      ,3562
Gender       -,0503
Educatio      ,0012
```

```
CompSize      ,0882
Familiar      ,2857
IT            ,0733
HR           -,0148

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3951      ,1561     3,3341     4,0427     7,0000   153,0000      ,0004

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,7976     1,2620     2,2169      ,0281      ,3045     5,2907
Drive         ,0713      ,0619     1,1507      ,2517     -,0511      ,1937
Gender       -,0541      ,3019     -,1793      ,8580     -,6506      ,5423
Educatio      ,0336      ,2567      ,1310      ,8960     -,4736      ,5408
CompSize      ,3046      ,2312     1,3174      ,1897     -,1522      ,7613
Familiar      ,3937      ,0839     4,6940      ,0000      ,2280      ,5594
IT            ,4286      ,4156     1,0312      ,3041     -,3925     1,2497
HR           -,2915      ,3374     -,8640      ,3889     -,9580      ,3750


************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps       c_cs
      ,0713      ,0619     1,1507      ,2517     -,0511      ,1937      ,0367      ,0888

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps      c'_cs
      ,0634      ,0577     1,0984      ,2738     -,0506      ,1774      ,0326      ,0790

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0079      ,0261     -,0419      ,0622

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0041      ,0133     -,0215      ,0314

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
GlobRepl      ,0099      ,0319     -,0518      ,0752

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

## *Appendix C1. Techical skills → GlobalSubstit → Att_AI (Ttrust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : TechSkil
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3707      ,1374     2,3207     3,4829     7,0000   153,0000      ,0017

Model
              coeff         se          t          p       LLCI       ULCI
constant    -3,2113     1,0533    -3,0487      ,0027    -5,2923    -1,1303
TechSkil      ,2810      ,0845     3,3254      ,0011      ,1141      ,4479
Gender        ,1945      ,2550      ,7628      ,4468     -,3092      ,6982
Educatio      ,0514      ,2135      ,2406      ,8102     -,3703      ,4731
CompSize      ,0683      ,1877      ,3640      ,7164     -,3025      ,4392
Familiar      ,1240      ,0718     1,7269      ,0862     -,0179      ,2659
IT            ,0760      ,3462      ,2195      ,8265     -,6079      ,7599
HR           -,4484      ,2828    -1,5857      ,1149    -1,0070      ,1102

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6400      ,4096     2,3793    10,4058    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,4540     1,1468     3,8839      ,0002     2,1881     6,7200
TechSkil      ,1243      ,0933     1,3329      ,1846     -,0600      ,3086
GlobRepl      ,2836      ,0836     3,3937      ,0009      ,1185      ,4487
TrustBen      ,2936      ,0804     3,6517      ,0004      ,1347      ,4524
Int_1        -,1567      ,0395    -3,9624      ,0001     -,2348     -,0786
Gender       -,3393      ,2595    -1,3076      ,1930     -,8519      ,1734
Educatio      ,1107      ,2181      ,5076      ,6125     -,3203      ,5417
CompSize      ,1063      ,1910      ,5566      ,5786     -,2711      ,4837
Familiar      ,2048      ,0752     2,7223      ,0073      ,0561      ,3534
IT            ,2182      ,3518      ,6202      ,5361     -,4770      ,9134
HR           -,0216      ,2887     -,0747      ,9406     -,5920      ,5489

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0618    15,7006     1,0000   150,0000      ,0001
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)

Conditional effects of the focal predictor at values of the moderator(s):

   TrustBen     Effect         se          t          p       LLCI       ULCI
    -1,9441      ,5882      ,1055     5,5742      ,0000      ,3797      ,7967
      ,0559      ,2748      ,0839     3,2759      ,0013      ,1091      ,4406
     2,0559     -,0386      ,1243     -,3102      ,7568     -,2842      ,2070

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,6631    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,0582      ,2018     5,2433      ,0000      ,6594     1,4570
```

```
    -4,5441      ,9955      ,1875     5,3093      ,0000      ,6250     1,3661
    -4,1441      ,9329      ,1735     5,3781      ,0000      ,5901     1,2756
    -3,7441      ,8702      ,1597     5,4477      ,0000      ,5546     1,1858
    -3,3441      ,8075      ,1464     5,5145      ,0000      ,5182     1,0969
    -2,9441      ,7449      ,1337     5,5715      ,0000      ,4807     1,0090
    -2,5441      ,6822      ,1217     5,6071      ,0000      ,4418      ,9226
    -2,1441      ,6195      ,1106     5,6016      ,0000      ,4010      ,8380
    -1,7441      ,5568      ,1008     5,5240      ,0000      ,3577      ,7560
    -1,3441      ,4942      ,0927     5,3314      ,0000      ,3110      ,6773
     -,9441      ,4315      ,0867     4,9752      ,0000      ,2601      ,6029
     -,5441      ,3688      ,0834     4,4232      ,0000      ,2041      ,5336
     -,1441      ,3061      ,0830     3,6899      ,0003      ,1422      ,4701
      ,2559      ,2435      ,0855     2,8466      ,0050      ,0745      ,4125
      ,6559      ,1808      ,0908     1,9908      ,0483      ,0014      ,3602
      ,6631      ,1797      ,0909     1,9759      ,0500      ,0000      ,3593
     1,0559      ,1181      ,0984     1,2006      ,2318     -,0763      ,3125
     1,4559      ,0555      ,1078      ,5146      ,6076     -,1575      ,2684
     1,8559     -,0072      ,1185     -,0609      ,9515     -,2414      ,2269
     2,2559     -,0699      ,1303     -,5364      ,5925     -,3274      ,1876
     2,6559     -,1326      ,1429     -,9279      ,3550     -,4149      ,1497
     3,0559     -,1952      ,1560    -1,2513      ,2128     -,5035      ,1131

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,4216
      ,6273    -1,9441     6,5980
     1,6273    -1,9441     7,1862
    -1,3727      ,0559     6,4389
      ,6273      ,0559     6,9886
     1,6273      ,0559     7,2634
    -1,3727     2,0559     7,4563
      ,6273     2,0559     7,3791
     1,6273     2,0559     7,3406
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,1243      ,0933     1,3329      ,1846     -,0600      ,3086

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 TechSkil    ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,1653      ,0647      ,0584      ,3098
      ,0559      ,0772      ,0358      ,0204      ,1596
     2,0559     -,0108      ,0373     -,0879      ,0641

      Index of moderated mediation:
            Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0440      ,0194     -,0874     -,0121
---

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix C2 Social skills->GlobalSubstit->Att_AI (trust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : SocSkill
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4032      ,1626     2,2530     4,2443     7,0000   153,0000      ,0003

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,9144      ,9994    -2,9161      ,0041    -4,8889     -,9400
SocSkill      ,2533      ,0633     3,9984      ,0001      ,1281      ,3784
Gender        ,2920      ,2482     1,1767      ,2412     -,1983      ,7824
Educatio      ,1755      ,2122      ,8273      ,4094     -,2437      ,5948
CompSize     -,0377      ,1875     -,2008      ,8411     -,4081      ,3328
Familiar      ,1604      ,0688     2,3307      ,0211      ,0244      ,2963
IT           -,0567      ,3434     -,1653      ,8690     -,7351      ,6216
HR           -,2173      ,2887     -,7526      ,4528     -,7877      ,3531

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6450      ,4160     2,3533    10,6863    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,4861     1,0791     4,1571      ,0001     2,3538     6,6184
SocSkill      ,1301      ,0700     1,8581      ,0651     -,0082      ,2684
GlobRepl      ,2628      ,0846     3,1052      ,0023      ,0956      ,4301
TrustBen      ,2883      ,0791     3,6431      ,0004      ,1319      ,4446
Int_1        -,1658      ,0387    -4,2798      ,0000     -,2423     -,0892
Gender       -,2982      ,2560    -1,1649      ,2459     -,8039      ,2076
Educatio      ,1807      ,2190      ,8252      ,4105     -,2520      ,6135
CompSize      ,0514      ,1920      ,2679      ,7892     -,3280      ,4309
Familiar      ,2223      ,0743     2,9899      ,0033      ,0754      ,3692
IT            ,1514      ,3516      ,4307      ,6673     -,5433      ,8462
HR            ,0946      ,2963      ,3194      ,7499     -,4908      ,6800

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0713    18,3164     1,0000   150,0000      ,0000
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)

Conditional effects of the focal predictor at values of the moderator(s):

   TrustBen     Effect         se          t          p       LLCI       ULCI
```

```
    -1,9441      ,5851      ,1034     5,6559      ,0000      ,3807      ,7895
      ,0559      ,2536      ,0850     2,9820      ,0033      ,0855      ,4216
     2,0559     -,0780      ,1255     -,6212      ,5354     -,3260      ,1701

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,5115    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,0824      ,1960     5,5226      ,0000      ,6951     1,4697
    -4,5441     1,0161      ,1821     5,5800      ,0000      ,6563     1,3759
    -4,1441      ,9498      ,1685     5,6376      ,0000      ,6169     1,2827
    -3,7441      ,8835      ,1552     5,6923      ,0000      ,5768     1,1902
    -3,3441      ,8172      ,1424     5,7392      ,0000      ,5358     1,0985
    -2,9441      ,7509      ,1301     5,7693      ,0000      ,4937     1,0080
    -2,5441      ,6846      ,1187     5,7683      ,0000      ,4501      ,9191
    -2,1441      ,6183      ,1082     5,7135      ,0000      ,4044      ,8321
    -1,7441      ,5519      ,0991     5,5713      ,0000      ,3562      ,7477
    -1,3441      ,4856      ,0917     5,2987      ,0000      ,3045      ,6667
     -,9441      ,4193      ,0864     4,8532      ,0000      ,2486      ,5901
     -,5441      ,3530      ,0837     4,2160      ,0000      ,1876      ,5185
     -,1441      ,2867      ,0839     3,4179      ,0008      ,1210      ,4525
      ,2559      ,2204      ,0868     2,5378      ,0122      ,0488      ,3920
      ,5115      ,1780      ,0901     1,9759      ,0500      ,0000      ,3560
      ,6559      ,1541      ,0923     1,6686      ,0973     -,0284      ,3366
     1,0559      ,0878      ,1000      ,8781      ,3813     -,1098      ,2853
     1,4559      ,0215      ,1093      ,1965      ,8445     -,1944      ,2374
     1,8559     -,0448      ,1199     -,3740      ,7089     -,2817      ,1920
     2,2559     -,1111      ,1314     -,8457      ,3991     -,3708      ,1485
     2,6559     -,1775      ,1437    -1,2346      ,2189     -,4615      ,1066
     3,0559     -,2438      ,1566    -1,5565      ,1217     -,5532      ,0657

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,4426
      ,6273    -1,9441     6,6128
     1,6273    -1,9441     7,1979
    -1,3727      ,0559     6,4742
      ,6273      ,0559     6,9813
     1,6273      ,0559     7,2349
    -1,3727     2,0559     7,5059
      ,6273     2,0559     7,3499
     1,6273     2,0559     7,2719
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,1301      ,0700     1,8581      ,0651     -,0082      ,2684

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 SocSkill    ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,1482      ,0531      ,0603      ,2684
      ,0559      ,0642      ,0315      ,0171      ,1386
     2,0559     -,0198      ,0356     -,0894      ,0515

      Index of moderated mediation:
             Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0420      ,0162     -,0783     -,0148
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000
```

```
Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix C3 Intuitive->GlobalSubstit->Att_AI (trust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : Intuitio
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3651      ,1333     2,3319     3,3608     7,0000   153,0000      ,0023

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,1392      ,9899    -2,1611      ,0322    -4,0949     -,1836
Intuitio      ,1515      ,0473     3,2043      ,0016      ,0581      ,2449
Gender        ,1648      ,2575      ,6399      ,5232     -,3440      ,6736
Educatio      ,0486      ,2140      ,2272      ,8206     -,3742      ,4714
CompSize     -,0607      ,1937     -,3133      ,7545     -,4433      ,3219
Familiar      ,1610      ,0701     2,2968      ,0230      ,0225      ,2995
IT            ,0802      ,3470      ,2311      ,8176     -,6053      ,7657
HR           -,4525      ,2834    -1,5965      ,1125    -1,0124      ,1075

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6346      ,4027     2,4068    10,1148    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,1072     1,0424     4,8997      ,0000     3,0476     7,1668
Intuitio      ,0101      ,0513      ,1964      ,8445     -,0913      ,1115
GlobRepl      ,3006      ,0841     3,5750      ,0005      ,1344      ,4667
TrustBen      ,3196      ,0796     4,0144      ,0001      ,1623      ,4769
Int_1        -,1646      ,0396    -4,1511      ,0001     -,2429     -,0862
Gender       -,3044      ,2627    -1,1587      ,2484     -,8234      ,2147
Educatio      ,1206      ,2194      ,5497      ,5833     -,3129      ,5541
CompSize      ,0955      ,1969      ,4847      ,6286     -,2937      ,4846
Familiar      ,2169      ,0751     2,8864      ,0045      ,0684      ,3654
IT            ,2158      ,3539      ,6098      ,5429     -,4834      ,9150
HR           -,0413      ,2904     -,1423      ,8870     -,6151      ,5324

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0686    17,2318     1,0000   150,0000      ,0001
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)

Conditional effects of the focal predictor at values of the moderator(s):
```

```
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -1,9441      ,6206      ,1058     5,8651      ,0000      ,4115      ,8296
      ,0559      ,2914      ,0844     3,4516      ,0007      ,1246      ,4582
     2,0559     -,0378      ,1250     -,3023      ,7628     -,2849      ,2093

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,7165    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,1143      ,2022     5,5115      ,0000      ,7148     1,5138
    -4,5441     1,0485      ,1878     5,5817      ,0000      ,6773     1,4196
    -4,1441      ,9827      ,1738     5,6550      ,0000      ,6393     1,3260
    -3,7441      ,9168      ,1600     5,7291      ,0000      ,6006     1,2330
    -3,3441      ,8510      ,1467     5,8002      ,0000      ,5611     1,1409
    -2,9441      ,7851      ,1340     5,8611      ,0000      ,5205     1,0498
    -2,5441      ,7193      ,1219     5,8993      ,0000      ,4784      ,9602
    -2,1441      ,6535      ,1109     5,8938      ,0000      ,4344      ,8725
    -1,7441      ,5876      ,1011     5,8123      ,0000      ,3879      ,7874
    -1,3441      ,5218      ,0930     5,6093      ,0000      ,3380      ,7056
     -,9441      ,4560      ,0871     5,2343      ,0000      ,2838      ,6281
     -,5441      ,3901      ,0838     4,6542      ,0000      ,2245      ,5558
     -,1441      ,3243      ,0835     3,8852      ,0002      ,1594      ,4892
      ,2559      ,2585      ,0861     3,0023      ,0031      ,0884      ,4286
      ,6559      ,1926      ,0914     2,1069      ,0368      ,0120      ,3733
      ,7165      ,1827      ,0924     1,9759      ,0500      ,0000      ,3653
     1,0559      ,1268      ,0990     1,2802      ,2024     -,0689      ,3225
     1,4559      ,0610      ,1085      ,5620      ,5749     -,1533      ,2752
     1,8559     -,0049      ,1192     -,0410      ,9674     -,2405      ,2307
     2,2559     -,0707      ,1311     -,5396      ,5903     -,3297      ,1882
     2,6559     -,1366      ,1437     -,9505      ,3434     -,4204      ,1473
     3,0559     -,2024      ,1569    -1,2903      ,1989     -,5123      ,1076

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,3322
      ,6273    -1,9441     6,5733
     1,6273    -1,9441     7,1939
    -1,3727      ,0559     6,4232
      ,6273      ,0559     7,0060
     1,6273      ,0559     7,2974
    -1,3727     2,0559     7,5142
      ,6273     2,0559     7,4386
     1,6273     2,0559     7,4008
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0101      ,0513      ,1964      ,8445     -,0913      ,1115

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Intuitio    ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,0940      ,0355      ,0323      ,1715
      ,0559      ,0441      ,0198      ,0121      ,0896
     2,0559     -,0057      ,0207     -,0487      ,0380

      Index of moderated mediation:
              Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0249      ,0106     -,0493     -,0075
---

********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix C4 Learning->GlobalSubstit->Att_AI (trust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : Learning
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3050      ,0931     2,4401     2,2426     7,0000   153,0000      ,0337

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,3074     1,0285    -2,2434      ,0263    -4,3394     -,2754
Learning      ,1055      ,0606     1,7400      ,0839     -,0143      ,2253
Gender        ,2718      ,2603     1,0443      ,2980     -,2424      ,7860
Educatio      ,0570      ,2189      ,2605      ,7948     -,3754      ,4894
CompSize      ,0386      ,1944      ,1983      ,8431     -,3455      ,4226
Familiar      ,1580      ,0728     2,1719      ,0314      ,0143      ,3018
IT            ,0585      ,3558      ,1645      ,8696     -,6445      ,7615
HR          -,4239      ,2961    -1,4318      ,1542    -1,0088      ,1610

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6350      ,4032     2,4049    10,1351    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,0285     1,0661     4,7168      ,0000     2,9220     7,1350
Learning      ,0252      ,0630      ,3996      ,6900     -,0994      ,1497
GlobRepl      ,3014      ,0828     3,6386      ,0004      ,1377      ,4650
TrustBen      ,3152      ,0801     3,9339      ,0001      ,1569      ,4735
Int_1       -,1639      ,0394    -4,1562      ,0001     -,2418     -,0860
Gender      -,3066      ,2602    -1,1781      ,2406     -,8207      ,2076
Educatio      ,1195      ,2192      ,5449      ,5866     -,3137      ,5527
CompSize      ,0948      ,1934      ,4904      ,6246     -,2873      ,4769
Familiar      ,2137      ,0754     2,8337      ,0052      ,0647      ,3628
IT            ,2083      ,3542      ,5880      ,5574     -,4916      ,9081
HR          -,0199      ,2963     -,0672      ,9465     -,6054      ,5655

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0687    17,2737     1,0000   150,0000      ,0001
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)

Conditional effects of the focal predictor at values of the moderator(s):
```

```
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -1,9441      ,6200      ,1032     6,0051      ,0000      ,4160      ,8240
      ,0559      ,2922      ,0832     3,5114      ,0006      ,1278      ,4566
     2,0559     -,0356      ,1250     -,2849      ,7761     -,2827      ,2114

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,7293    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,1118      ,1990     5,5871      ,0000      ,7186     1,5049
    -4,5441     1,0462      ,1847     5,6638      ,0000      ,6812     1,4112
    -4,1441      ,9806      ,1707     5,7444      ,0000      ,6433     1,3179
    -3,7441      ,9151      ,1570     5,8269      ,0000      ,6048     1,2254
    -3,3441      ,8495      ,1438     5,9074      ,0000      ,5654     1,1336
    -2,9441      ,7839      ,1311     5,9784      ,0000      ,5248     1,0430
    -2,5441      ,7184      ,1192     6,0268      ,0000      ,4829      ,9539
    -2,1441      ,6528      ,1083     6,0304      ,0000      ,4389      ,8667
    -1,7441      ,5872      ,0986     5,9543      ,0000      ,3924      ,7821
    -1,3441      ,5217      ,0907     5,7493      ,0000      ,3424      ,7010
     -,9441      ,4561      ,0851     5,3615      ,0000      ,2880      ,6242
     -,5441      ,3905      ,0821     4,7575      ,0000      ,2283      ,5527
     -,1441      ,3250      ,0821     3,9590      ,0001      ,1628      ,4872
      ,2559      ,2594      ,0851     3,0498      ,0027      ,0913      ,4275
      ,6559      ,1939      ,0907     2,1368      ,0342      ,0146      ,3731
      ,7293      ,1818      ,0920     1,9759      ,0500      ,0000      ,3636
     1,0559      ,1283      ,0986     1,3010      ,1952     -,0665      ,3231
     1,4559      ,0627      ,1082      ,5795      ,5631     -,1511      ,2766
     1,8559     -,0028      ,1192     -,0239      ,9810     -,2383      ,2326
     2,2559     -,0684      ,1311     -,5218      ,6026     -,3274      ,1906
     2,6559     -,1340      ,1438     -,9318      ,3529     -,4181      ,1501
     3,0559     -,1995      ,1570    -1,2709      ,2057     -,5098      ,1107

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,3410
      ,6273    -1,9441     6,5811
     1,6273    -1,9441     7,2011
    -1,3727      ,0559     6,4214
      ,6273      ,0559     7,0058
     1,6273      ,0559     7,2980
    -1,3727     2,0559     7,5017
      ,6273     2,0559     7,4305
     1,6273     2,0559     7,3949
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0252      ,0630      ,3996      ,6900     -,0994      ,1497

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Learning    ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,0654      ,0450     -,0155      ,1618
      ,0559      ,0308      ,0234     -,0071      ,0842
     2,0559     -,0038      ,0161     -,0370      ,0316

      Index of moderated mediation:
              Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0173      ,0122     -,0441      ,0039
---

********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix C5 Autocorrection->GlobalSubstit->Att_AI (trust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : Autocorr
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3033      ,0920     2,4430     2,2142     7,0000   153,0000      ,0360

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,5453     1,0657    -2,3883      ,0181    -4,6507     -,4398
Autocorr      ,0995      ,0590     1,6865      ,0937     -,0171      ,2160
Gender        ,3085      ,2586     1,1932      ,2346     -,2023      ,8194
Educatio      ,0883      ,2195      ,4024      ,6880     -,3454      ,5220
CompSize      ,0467      ,1940      ,2408      ,8100     -,3365      ,4300
Familiar      ,1668      ,0720     2,3164      ,0219      ,0245      ,3091
IT            ,1423      ,3558      ,3999      ,6898     -,5606      ,8451
HR          -,5122      ,2892    -1,7713      ,0785    -1,0836      ,0591

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6423      ,4125     2,3673    10,5338    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,4773     1,1041     4,0552      ,0001     2,2958     6,6589
Autocorr      ,0970      ,0608     1,5941      ,1130     -,0232      ,2172
GlobRepl      ,2957      ,0821     3,5997      ,0004      ,1334      ,4580
TrustBen      ,2988      ,0786     3,8017      ,0002      ,1435      ,4541
Int_1       -,1531      ,0397    -3,8595      ,0002     -,2314     -,0747
Gender      -,3020      ,2568    -1,1760      ,2415     -,8093      ,2054
Educatio      ,1381      ,2176      ,6348      ,5266     -,2919      ,5682
CompSize      ,0740      ,1914      ,3863      ,6998     -,3043      ,4522
Familiar      ,2126      ,0745     2,8512      ,0050      ,0653      ,3599
IT            ,2646      ,3523      ,7510      ,4538     -,4315      ,9607
HR          -,0297      ,2876     -,1032      ,9180     -,5980      ,5386

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0583    14,8960     1,0000   150,0000      ,0002
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)
```

```
Conditional effects of the focal predictor at values of the moderator(s):

   TrustBen     Effect         se          t          p       LLCI       ULCI
    -1,9441      ,5933      ,1034     5,7353      ,0000      ,3889      ,7977
      ,0559      ,2871      ,0825     3,4795      ,0007      ,1241      ,4502
     2,0559     -,0190      ,1245     -,1528      ,8788     -,2650      ,2270

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,7488    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,0525      ,2003     5,2538      ,0000      ,6567     1,4483
    -4,5441      ,9912      ,1859     5,3313      ,0000      ,6239     1,3586
    -4,1441      ,9300      ,1718     5,4135      ,0000      ,5906     1,2695
    -3,7441      ,8688      ,1580     5,4991      ,0000      ,5566     1,1810
    -3,3441      ,8076      ,1446     5,5846      ,0000      ,5218     1,0933
    -2,9441      ,7463      ,1318     5,6638      ,0000      ,4860     1,0067
    -2,5441      ,6851      ,1197     5,7250      ,0000      ,4486      ,9216
    -2,1441      ,6239      ,1085     5,7479      ,0000      ,4094      ,8383
    -1,7441      ,5626      ,0987     5,6998      ,0000      ,3676      ,7577
    -1,3441      ,5014      ,0906     5,5334      ,0000      ,3224      ,6805
     -,9441      ,4402      ,0847     5,1944      ,0000      ,2727      ,6076
     -,5441      ,3790      ,0816     4,6454      ,0000      ,2178      ,5402
     -,1441      ,3177      ,0814     3,9016      ,0001      ,1568      ,4786
      ,2559      ,2565      ,0843     3,0416      ,0028      ,0899      ,4231
      ,6559      ,1953      ,0900     2,1703      ,0316      ,0175      ,3731
      ,7488      ,1811      ,0916     1,9759      ,0500      ,0000      ,3621
     1,0559      ,1341      ,0979     1,3694      ,1729     -,0594      ,3275
     1,4559      ,0728      ,1076      ,6769      ,4995     -,1397      ,2854
     1,8559      ,0116      ,1186      ,0977      ,9223     -,2228      ,2459
     2,2559     -,0496      ,1306     -,3800      ,7045     -,3077      ,2085
     2,6559     -,1109      ,1434     -,7731      ,4407     -,3942      ,1725
     3,0559     -,1721      ,1567    -1,0980      ,2740     -,4818      ,1376

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,4019
      ,6273    -1,9441     6,5885
     1,6273    -1,9441     7,1817
    -1,3727      ,0559     6,4198
      ,6273      ,0559     6,9940
     1,6273      ,0559     7,2812
    -1,3727     2,0559     7,4376
      ,6273     2,0559     7,3996
     1,6273     2,0559     7,3806
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0970      ,0608     1,5941      ,1130     -,0232      ,2172

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Autocorr    ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,0590      ,0402     -,0129      ,1444
      ,0559      ,0286      ,0204     -,0067      ,0754
     2,0559     -,0019      ,0148     -,0353      ,0277

      Index of moderated mediation:
             Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0152      ,0112     -,0400      ,0033
---

*********************** ANALYSIS NOTES AND ERRORS ************************
```

```
Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```

*Appendix C6 Drive->GlobalSubstit->Att_AI (trust as moderator in step 2)*

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Version 3.2.01 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 14
    Y  : Att_AI
    X  : Drive
    M  : GlobRepl
    W  : TrustBen

Covariates:
 Gender   Educatio CompSize Familiar IT       HR

Sample
Size:  161

**************************************************************************
OUTCOME VARIABLE:
 GlobRepl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2753      ,0758     2,4865     1,7931     7,0000   153,0000      ,0924

Model
              coeff         se          t          p       LLCI       ULCI
constant    -2,1123     1,0898    -1,9382      ,0544    -4,2653      ,0407
Drive         ,0183      ,0535      ,3427      ,7323    -,0874      ,1240
Gender        ,3265      ,2607     1,2523      ,2124    -,1886      ,8416
Educatio      ,0686      ,2217      ,3095      ,7573    -,3694      ,5066
CompSize      ,1028      ,1997      ,5146      ,6075    -,2917      ,4972
Familiar      ,1801      ,0724     2,4858      ,0140      ,0370      ,3232
IT            ,1122      ,3589      ,3126      ,7550    -,5969      ,8213
HR          -,5377      ,2913    -1,8457      ,0669    -1,1133      ,0378

**************************************************************************
OUTCOME VARIABLE:
 Att_AI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6357      ,4041     2,4014    10,1715    10,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,8862     1,1082     4,4091      ,0000     2,6965     7,0759
Drive         ,0326      ,0530      ,6142      ,5400    -,0722      ,1374
GlobRepl      ,3038      ,0826     3,6789      ,0003      ,1406      ,4670
TrustBen      ,3167      ,0783     4,0424      ,0001      ,1619      ,4715
Int_1       -,1653      ,0391    -4,2249      ,0000    -,2427    -,0880
Gender      -,3006      ,2587    -1,1618      ,2471    -,8117      ,2106
Educatio      ,1329      ,2196      ,6051      ,5460    -,3011      ,5669
CompSize      ,1336      ,1979      ,6753      ,5005    -,2574      ,5246
Familiar      ,2139      ,0752     2,8450      ,0051      ,0653      ,3624
IT            ,2319      ,3545      ,6543      ,5139    -,4685      ,9323
HR          -,0434      ,2895    -,1501      ,8809    -,6155      ,5286

Product terms key:
 Int_1    :        GlobRepl x        TrustBen

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
M*W      ,0709    17,8495     1,0000   150,0000      ,0000
----------
    Focal predict: GlobRepl (M)
          Mod var: TrustBen (W)

Conditional effects of the focal predictor at values of the moderator(s):

   TrustBen     Effect         se          t          p       LLCI       ULCI
```

```
    -1,9441      ,6252      ,1021     6,1221      ,0000      ,4234      ,8270
      ,0559      ,2945      ,0830     3,5494      ,0005      ,1306      ,4585
     2,0559    -,0361      ,1249     -,2893      ,7727     -,2829      ,2106

Moderator value(s) defining Johnson-Neyman significance region(s):
      Value    % below    % above
      ,7371    62,1118    37,8882

Conditional effect of focal predictor at values of the moderator:
   TrustBen     Effect         se          t          p       LLCI       ULCI
    -4,9441     1,1212      ,1968     5,6983      ,0000      ,7325     1,5100
    -4,5441     1,0551      ,1826     5,7774      ,0000      ,6943     1,4160
    -4,1441      ,9890      ,1688     5,8604      ,0000      ,6555     1,3224
    -3,7441      ,9228      ,1552     5,9452      ,0000      ,6161     1,2295
    -3,3441      ,8567      ,1421     6,0277      ,0000      ,5759     1,1375
    -2,9441      ,7906      ,1296     6,1001      ,0000      ,5345     1,0466
    -2,5441      ,7244      ,1178     6,1486      ,0000      ,4916      ,9572
    -2,1441      ,6583      ,1070     6,1499      ,0000      ,4468      ,8698
    -1,7441      ,5922      ,0976     6,0678      ,0000      ,3993      ,7850
    -1,3441      ,5260      ,0899     5,8518      ,0000      ,3484      ,7036
     -,9441      ,4599      ,0844     5,4477      ,0000      ,2931      ,6267
     -,5441      ,3938      ,0816     4,8238      ,0000      ,2325      ,5550
     -,1441      ,3276      ,0818     4,0056      ,0001      ,1660      ,4892
      ,2559      ,2615      ,0849     3,0803      ,0025      ,0937      ,4292
      ,6559      ,1953      ,0906     2,1556      ,0327      ,0163      ,3744
      ,7371      ,1819      ,0921     1,9759      ,0500      ,0000      ,3638
     1,0559      ,1292      ,0985     1,3113      ,1918     -,0655      ,3239
     1,4559      ,0631      ,1081      ,5832      ,5606     -,1506      ,2768
     1,8559     -,0031      ,1191     -,0257      ,9795     -,2383      ,2322
     2,2559     -,0692      ,1309     -,5285      ,5979     -,3279      ,1895
     2,6559     -,1353      ,1435     -,9430      ,3472     -,4189      ,1482
     3,0559     -,2015      ,1567    -1,2860      ,2004     -,5110      ,1081

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   GlobRepl   TrustBen   Att_AI     .
BEGIN DATA.
    -1,3727    -1,9441     5,3319
      ,6273    -1,9441     6,5824
     1,6273    -1,9441     7,2076
    -1,3727      ,0559     6,4192
      ,6273      ,0559     7,0083
     1,6273      ,0559     7,3029
    -1,3727     2,0559     7,5065
      ,6273     2,0559     7,4343
     1,6273     2,0559     7,3981
END DATA.
GRAPH/SCATTERPLOT=
 GlobRepl WITH     Att_AI   BY       TrustBen .

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0326      ,0530      ,6142      ,5400     -,0722      ,1374

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 Drive       ->    GlobRepl    ->    Att_AI

   TrustBen     Effect     BootSE   BootLLCI   BootULCI
    -1,9441      ,0115      ,0370     -,0669      ,0812
      ,0559      ,0054      ,0179     -,0285      ,0428
     2,0559     -,0007      ,0085     -,0142      ,0224

      Index of moderated mediation:
              Index     BootSE   BootLLCI   BootULCI
TrustBen     -,0030      ,0100     -,0205      ,0203
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000
```

```
Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TrustBen GlobRepl

NOTE: Variables names longer than eight characters can produce incorrect output.
      Shorter variable names are recommended.

------ END MATRIX -----
```