Prospective Physicians' Intention to Adopt Artificial Intelligence: A Configurational Perspective

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Abstract

Artificial intelligence (AI) drives transformation across medical specialities, requiring current and future generations of physicians to navigate ever-changing digital environments. In this context, prospective physicians will play a key role in adopting and applying AI-based health technologies, underlining the importance of understanding their knowledge, attitudes, and intentions toward AI. To dissociate corresponding profiles, we adopted a configurational perspective and conducted a two-stage survey study of 184 (t_0) and 138 (t_1) medical students at a Canadian medical school. Our principal findings corroborate the existence of distinct clusters in respondents' AI profiles. We refer to these profiles as the AI unfamiliar, the AI educated, and the AI positive, showing that each profile is associated with different intentions towards future AI use. These exploratory insights on the variety of AI profiles in prospective physicians underline the need for targeted and adaptive measures of education and outreach.

Keywords: medical students, artificial intelligence, intentions, attitudes, beliefs, knowledge, survey.

1. Introduction

Artificial intelligence (AI), which is broadly defined as the use of a computer to model intelligent behavior with minimal human intervention (Hamet & Tremblay, 2017), has the potential to transform or even revolutionize medicine (Briganti & Le Moine, 2020). In his seminal book "Deep medicine: how artificial intelligence can make health care human again," Topol (2019) highlights AI's potential to improve the lives of doctors and patients. The promise of clinical AI algorithms ranges from image-based diagnosis in radiology, ophthalmology, and dermatology (Haenssle et al., 2020; Lakhani & Sundaram, 2017; Li et al., 2018), to patient monitoring in cardiology and endocrinology (Christiansen et al., 2017; Halcox et al., 2017), and to prediction of cardiovascular and kidney diseases (Huang et al., 2017; Niel et al., 2018), to name but a few.

For the potential benefits associated with AI usage to materialize to their full potential, both current and future generations of physicians must be able to navigate with ease in an ever-changing digital environment. Accordingly, a growing academic literature has emerged on the attitudes of physicians toward AI, most of which concerns radiologists. According to these studies, the perception of AI among this group of specialists ranged between acceptance with enthusiasm and skepticism for fears of being displaced by the technology, a relation that was attenuated by exposure and learning about the impacts of AI (European Society of Radiology, 2019; Pakdemirli, 2019; Santomartino, 2022).

Other surveys concerned all physicians, irrespective of their specialty. For instance, Oh and colleagues (2019) surveyed 669 physicians practicing in South Korea. While most respondents considered AI useful in medical practice, only 6% said that they had good familiarity with this technology. The main advantage of using AI was seen as the ability to analyze vast amounts of high-quality, clinically relevant data in real time and a vast majority of respondents (83%) agreed that the area of medicine in which AI would be most useful is disease diagnosis.

Similar results have been reported with medical students, who, despite seeing AI in medicine favorably, still show concerns about how AI will affect their future career, especially for specialties relying on image analysis, a task for which AI-based algorithms have shown great promises (Park et al., 2021; Pinto Dos Santos et al., 2019; Santomartino, 2022; Sit et al., 2020). Specifically, Scheetz et al. (2021) conducted an online survey of 632 fellows and trainees of three specialties (i.e., ophthalmology, radiology/radiation oncology, and dermatology) in Australia and New Zealand. Findings reveal that 71% of respondents believed AI would improve their medical specialty, and 86% felt that medical workforce needs would be impacted by AI within the next decade. Yet, 81% had never used AI in their clinical practice and most considered their AI-related knowledge as average or below average.

While only 2% of physicians in Canada are using AI for patient care purposes (Infoway, 2022), a recent survey of Canadian family physicians show that a slight majority (55% of 768 respondents) would be open to using AI for medical diagnosis purposes in the future (Paré et al., 2022a). Only one study having examined medical students' intention to use AI in their future practice has been found. Using self-reported data from 211 undergraduate medical students in Vietnam, Tran et al. (2021) observed a moderate level of intention to use an AI-based diagnosis support system in their future practice.

While education has been identified as a priority to prepare future physicians for the successful deployment of AI in healthcare (Dumić-Čule et al., 2020; Park et al., 2021; Scheetz et al., 2021), to our knowledge only a few studies have investigated medical students' attitudes toward AI and their opinion on the importance of introducing AI-related material as a standard part of the curriculum. For instance, Sit et al. (2020) explored the attitudes of 484 United Kingdom medical students regarding training in AI technologies, their understanding of AI, and career intention towards radiology. Findings revealed that medical students do not feel adequately prepared to work alongside AI but understand the increasing importance of AI in healthcare and would like to receive formal training on the subject. In a survey of Canadian medical students, who considered radiology as their speciality, a majority (68%) expected AI to reduce future demand for radiologists and some (29%) even expected it to replace radiologists in the future (Gong et al., 2019). These concerns draw attention to the need for educating and informing students about how AI can transform the profession and how it may enable viable careers in the long-term. As a final example, Park et al. (2021) surveyed 156 medical students in the United States. Over 75% agreed that AI would have a significant role in the future of medicine and 66% believed that diagnostic radiology would be the specialty most greatly impacted. Nearly half (44%) reported that AI made them less enthusiastic about radiology.

In short, while empirical knowledge is growing on medical students' views on AI (e.g., Gong et al., 2019; Grunhut et al., 2021; Park et al., 2021; Pinto Dos Santos et al., 2019; Santomartino, 2022), less is known about their familiarity with such technology (e.g., Gong et al., 2019; Reeder & Lee, 2022; Santomartino, 2022), and even less so about their intention to integrate AI in their future practice (e.g., Tran et al., 2021). Importantly, prior surveys soliciting medical students were conducted prior to the COVID-19 pandemic and are highly descriptive and atheoretical in nature. This exploratory study aims to fill these gaps. To do so, our first objective is to verify the existence of AI profiles among prospective physicians' (PPs) and to assess their respective influence on the students' intention to integrate AI in their practice. Our second goal is to investigate the effect of the COVID-19 pandemic on PPs' views on and intention toward AI. A two-stage survey of medical students in Quebec, Canada was conducted in line with those objectives.

1.1. Research model

A configurational (case-based) – as opposed to the universalistic (variable-based) – perspective is proposed here because it provides in our opinion a better understanding of the complex interdependencies among the determinants of an individual's behavioral intention. The research model in Figure 1 assumes that different AI profiles, that is, different patterns (or configurations) of endogenous and exogenous factors that characterize PPs with regard to AI, will be associated with different levels of behavioral intention towards AI. The configurational approach (Fiss et al., 2013) also assumes that the dimensions can have asymmetric and non-additive effects on a target variable (e.g., behavioral intention). This contrasts with traditional regression-based approaches, which are generally based on independent and additive effects. In this study, we seek to identify those AI profiles that are associated with a strong intent on the part of PPs to integrate AI in their future medical practice.

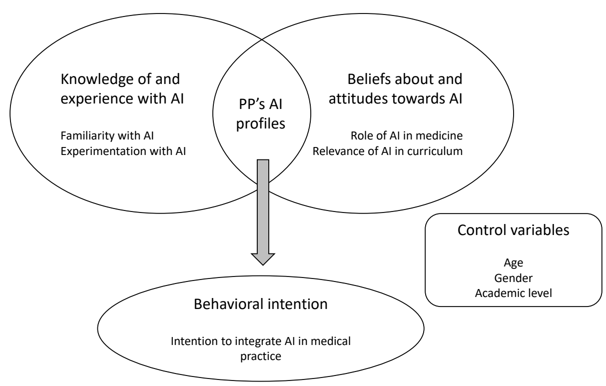

Figure 1. Configurational model

Our configurational model assumes that PPs' *AI profile* is composed of two main dimensions: (1) knowledge of and experience with AI and (2) beliefs about and attitudes toward AI. The configurational components were chosen both on a theoretical basis (presence in IS behavioral theories) and on an empirical basis (confirmed as a determinant of intention in IS behavioural research).

The first dimension refers to PPs' *familiarity* and *experimentation* with AI. In the present context, familiarity with AI is mainly within a student's own control (endogenous factor). It is closely related to the concept of computer self-efficacy (Compeau & Higgins, 1995) which is included in many information technology adoption models. For its part, experimentation with AI is largely influenced by external factors (exogenous factor). It is associated with the concept of "facilitating conditions" included in the technology acceptance model (TAM), a theory that models how potential users come to adopt a new technology (Davis, 1989). Facilitating conditions are external factors that influence an individual's perceptions of the difficulty with which a task (e.g., use of AI technologies) may be performed (Paré & Elam, 1995; Teo, 2010). In the present study, facilitating conditions are operationalized as medical students' level of hands-on experimentation with AI tools during their medical education.

The second dimension in our model concerns PPs' *beliefs* about and *attitudes* toward AI. According to Triandis' theory of interpersonal behavior, individuals' behavioral intention is influenced by their beliefs about the targeted behavior (Triandis, 1980). In this study, we measured medical students' beliefs about the potential impact of AI on the medical profession as well as on their own medical practice. This dimension also encompasses PPs' attitudes toward AI. Attitudes are related to another TAM variable, namely, perceived usefulness, which is defined as the degree to which a person believes that using a particular technology would enhance their performance (Davis, 1989). Adapted to the present study context, perceived usefulness refers to medical students' perceptions of the relevance of integrating AI-related material into the medical curriculum.

In short, the approach adopted here will allow us to group PPs in such a way that those showing the same AI profile are more similar to each other (in terms of the above two dimensions) than to those showing other profiles. Last, following prior research on digital health training (Vossen et al., 2020) as well as various studies testing the TAM (Venkatesh, 2000), three individual factors were included in our model as control variables, namely, gender, age, and academic level. Due to the exploratory nature of this study, we simply assert that these individual factors are likely to be associated with PPs' AI profiles, which in turn will be associated with their behavioral intention with regard to AI.

2. Methods

As part of a broader study of PPs' intention toward digital health technologies (Paré et al., 2022b), the present study was conducted at the University of Montréal's (UM) medical school in Québec, Canada. During the 5-year long undergraduate medical curriculum, no formal digital health education or training is provided to students. However, students have access to the EDUlib online training platform which offers educational content on a variety of subjects including health and information technologies, as well as to symposia and conferences on different aspects of digital health. The study population consisted of 1,367 UM medical students. The survey questionnaire was administered in two phases, that is, an initial survey (t_0) in February 2020, before the Covid-19 pandemic, and a replication survey (t_1) in January 2021, during the pandemic.

As we were unable to locate any pre-existing questionnaire that assessed the variables included in our research model, we developed our own instrument. The survey design underwent several rounds of iteration, and final validation was performed with a group of 10 UM medical students who were excluded from the sampling population. The survey questionnaire was approved by the UM's ethics committee.

The measurement of the research variables was based on the above-mentioned literature on medical education in digital health. The "experimentation with AI technologies", "familiarity with AI technologies" and "importance of AI in the medical curriculum" variables were each measured with three 5-point scales (artificial intelligence, machine learning, big data). The "role of AI in the future of medicine" variable was measured with five 5-point scales pertaining to the effects of AI on medical tasks (prevention, diagnosis, treatment, prognosis, patient-physician relationship) and nine 5-point scales pertaining to the effects of AI on medical specialties (pathology, radiology, dermatology, ophthalmology, emergency and critical care, family medicine, internal medicine, psychiatry). The "intention to use AI technologies" variable was measured as an "index", as opposed to "scale" (Babbie, 2009). This last measure was obtained by summing the PPs' eventual use (yes or no) of AI technologies in support of eight medical activities, namely: radiological image analysis, photographical image analysis, pathological image analysis, diagnosis, prognosis, therapeutic planning, patient history data analysis, evaluation, and monitoring of patient-physician communication.

The data were first analyzed with descriptive statistics and further examined through analysis of variance (ANOVA) and cluster analyses. The underlying goals of our cluster analyses, in line with the configurational perspective adopted in this study, were to gather the sampled PPs into different groups (clusters) such that PPs in the same cluster a) are highly similar and b) differ significantly from the PPs in the other clusters with regard to their knowledge of and experience with AI and with regard to their attitudes towards AI. By achieving such aims, cluster analysis derives configurations or profiles that each constitutes a coherent whole and is both interpretable and meaningful (Gan et al., 2007). The clustering algorithm chosen was SPSS's TwoStep algorithm, as it has been found to be the top-performing one (Gelbard et al., 2007). Moreover, this algorithm is well suited for large samples and the process of determining the optimal cluster solution (i.e., the optimal number of groups) is handled automatically by the SPSS algorithm.

3. Results

A total of 184 students responded to the initial survey at t_0 (13%), whereas 138 responded to the replication survey at t_1 (10%). More participants were female (65% at t_0 and 70% at t_1). The mean age was 23 years, which is comparable to the average age of medical students at UM. The reliability and descriptive statistics of the research variables for the two samples (t_0 and t_1) are presented in Table 1. When comparing the variable means between the t_0 and t_1 samples, a significant difference ($p < 0.05$) was found for a single variable, indicating that PPs at t_1 (peri-Covid-19) are less familiar with AI technologies, albeit slightly, than those at t_0 (pre-Covid-19). Overall, these two samples thus appear to be quite similar, notwithstanding the advent of the Covid-19 pandemic after the initial survey.

Table 1. Reliability, descriptive statistics, and comparison of research variables (t_0 and t_1)

Research Construct	**t_0** (n = 184)					**t_1** (n = 138)					**T**[b]
Research variable	α[a]	mean	stdev	min	max	α[a]	mean	stdev	min	max	
Knowledge and Experience of AI											
Familiarity with AI technologies	0.87	1.95	0.89	1.0	5.0	0.82	1.76	0.82	1.0	4.3	2.0*
Experimentation with AI technologies	0.66[c]	1.25	0.45	1.0	4.0	0.73	1.16	0.39	1.0	3.7	1.9
Attitude toward AI											
Importance of AI in the curriculum	0.84	3.52	0.76	1.0	5.0	0.84	3.50	0.71	1.0	5.0	0.3
Role of AI in the future of medicine	0.89	3.49	0.54	2.2	5.0	0.88	3.43	0.47	2.6	4.7	1.1
Individual Background											
Academic level	-	2.90	1.39	1	5	-	2.62	1.17	1	5	1.9
Age	-	22.9	3.4	18	38	-	22.6	2.6	18	35	1.0
Gender	-	0.65	0.48	0	1	-	0.69	0.45	0	1	0.9
Behavioral Intent with regard to AI											
Intention to integrate AI in med. practice	-	3.93	3.07	0	8	-	3.64	3.22	0	8	0.8

*: $p < 0.05$
[a]Cronbach's alpha coefficient of reliability [inappropriate for index variables]
[b]two-tailed T-test (comparison of the means)
[c]While slightly below .70, this value is deemed acceptable within the present analytical context (Bernardi, 1994).

3.1. Configurational analysis (t_0)

In answer to our research question and given our configurational view of PPs' behavioral intention with regard to AI (cf. Figure 1), we classified the 184 PPs in the initial sample (t_0) on the basis of their AI profile. This was done by performing a cluster analysis that used as clustering variables the two indicators of the PPs' knowledge of and experience with AI as well as the two indicators of their attitudes toward AI. Here, a two-cluster solution was found to be optimal when compared to three- and four-cluster solutions, corresponding to the two AI profiles presented in Table 2a. The PPs in the first group (n = 123) are characterized on average by a low level of knowledge of and experience with AI, and by neutral attitudes toward AI. They were thus labelled as *AI-Unfamiliar* prospective physicians. The PPs in the second group (n = 61) are characterized by a medium level of familiarity with AI technologies, by a low level of experimentation with these technologies, and by positive attitudes toward AI. There were thus labelled as *AI-Positive* prospective physicians. In Table 2b, we present the breakdown of the individual background and behavioral intention variables by AI profile. ANOVA results point to significant differences between the two profiles, as derived by the clustering algorithm, for variables that may be theoretically related to the profiles but are not used as clustering variables (Ketchen Jr. & Shook, 1996). First, one finds that female participants constitute a significantly greater proportion of PPs in the *AI-Positive* group (78%) than in the *AI-Unfamiliar* group (73%). Second, *AI-Positive* PPs show on average a definite intent to integrate AI in their future medical practice, whereas *AI-Unfamiliar* PPs are more guarded

Table 2a. Prospective physicians' AI profiles at t_0 (n = 184)

Clustering variable	PPs' AI profiles: *AI-Unfamiliar* (n = 123) mean	*AI-Positive* (n = 61) mean	ANOVA F
Knowledge and Experience of AI			
Familiarity with AI technologies	1.66 (low)	2.53 (med)	48.8***
Experimentation with AI technologies	1.11 (low)	1.54 (low)	43.3***
Attitude toward AI			
Importance of AI in the medical curriculum	3.20 (med)	4.15 (high)	93.6***
Role of AI in the future of medicine	3.21 (med)	4.04 (high)	196.7***
***: $p < 0.001$			

Table 2b. Characterization of the prospective physicians' AI profiles at t_0 (n = 184)

Individual/Behavioral attribute of the profiles	PPs' AI profiles: *AI-Unfamiliar* (n = 123) mean	*AI-Positive* (n = 61) mean	ANOVA F
Individual Background			
Academic level	3.21	2.56	2.1
Age	22.8	22.6	0.7
Gender	0.73	0.78	10.0**
Behavioral Intention with regard to AI			
Intention to integrate AI in medical practice	2.56 (low-med)	5.35 (med-high)	79.1***
**: $p < 0.01$ ***: $p < 0.001$			

Table 3a. Prospective physicians' AI profiles at t_1 (n = 138)

Clustering variable	PPs' AI profiles: *AI-Unfamiliar* (n = 55) Mean	*AI-Educated* (n = 30) mean	*AI-Positive* (n = 53) mean	ANOVA F
Knowledge and Experience of AI				
Familiarity with AI technologies	1.22_c (low)	2.70_a (high)	1.77_b (med)	58.4***
Experimentation with AI technologies	1.02_b (low)	1.56_a (high)	1.09_b (low)	28.0***
Attitude toward AI				
Importance of AI in the medical curriculum	2.96_c (med)	3.44_b (med)	4.08_a (high)	62.1***
Role of AI in the future of medicine	3.02_b (med)	3.21_b (med)	3.86_a (high)	80.0***
***: $p < 0.001$				
Nota. Within rows, different subscripts indicate significant ($p < 0.05$) pair-wise differences between means (Scheffé's post hoc test).				

Table 3b. Characterization of the prospective physicians' AI profiles at t_1 (n = 138)

Individual/Behavioral attribute of the profiles	PPs' AI profiles			ANOVA F
	AI-Unfamiliar (n = 55) mean	*AI-Educated* (n = 30) mean	*AI-Positive* (n = 53) mean	
Individual Background				
Academic level	2.78	2.50	2.53	0.8
Age	22.4	22.3	22.9	0.6
Gender	0.77	0.69	0.62	1.4
Behavioral Intention with regard to AI				
Intention to integrate AI in medical practice	1.75_c (low)	3.27_b (med)	5.83_a (high)	31.9***

***: $p < 0.001$

Nota. Within rows, different subscripts indicate significant ($p < 0.05$) pair-wise differences between means (Scheffé's post hoc test).

in this regard. This last result constitutes an illustration of the configurational approach's capacity to provide a better understanding of PPs' intentions toward AI, as compared to the 'variance' approach (Ragin et al., 1997). Indeed, such an understanding results from the systemic and holistic view taken in this study, wherein the PPs' AI profile, rather than individual AI-related variables, is related to their intentions toward AI.

3.2. Configurational analysis (t_1)

Similar to the initial survey, the 138 PPs sampled in the replication survey (t_1) were classified on the basis of their AI profile. As presented in Table 3a, a three-cluster solution was found to be optimal when compared to two- and four-cluster solutions, thus providing us with three meaningful and interpretable AI profiles. The PPs in the first group (n = 55) are characterized on average by a low level of knowledge of and experience with AI, and by neutral attitudes toward AI. They were thus again labelled as *AI-Unfamiliar* prospective physicians. The PPs in the second group (n = 30) are characterized by high levels of familiarity and experimentation with AI technologies, and by neutral attitudes toward AI. They were thus classified as *AI-Educated* prospective physicians. Last, the PPs in the third group (n = 53) are characterized by a medium level of familiarity with AI technologies, a low level of experimentation with these technologies, and by positive attitudes toward AI. There were thus again labelled as *AI-Positive* prospective physicians.

In Table 3b, we present the breakdown of the individual background and behavioral intention variables by AI profile. First, there appears to be no significant differences between the three AI profiles with regard to the PPs' individual background, that is, neither in terms of academic level, age, or gender. However, ANOVA results point to significant differences between the three AI profiles with regard to the sampled PPs' behavioral intention. First, the *AI-Unfamiliar* PPs, showing on average the lowest levels of familiarity and experimentation with AI technologies, are the ones who show the lowest intention to integrate AI in their medical practice. Conversely, *AI-Positive* PPs, showing the strongest beliefs in the importance of AI in the medical curriculum and in the role of AI in the future of medicine, are those who show the greatest intention to integrate AI in their future practice. On the other hand, *AI-Educated* PPs stand 'in-the-middle' with regard to their intentions with regard to the future of AI in medical practice, when compared to the other two groups. One may recall here that the *AI-Educated* group distinguishes itself from the other two by showing the greatest knowledge of and experience with AI, whereas this group shares neutral attitudes toward AI with the *AI-Unfamiliar* group. These last results illustrate yet again the capacity of the configurational approach to provide a better understanding of the four interconnected elements that constitute the AI profile of prospective physicians. That is, causal elements that bring about a future behavioral outcome with regard to AI and do so jointly and synergistically rather than individually and linearly.

3.3. Further analysis of the AI profiles

In Table 4, we present the results of multivariate regression analyses meant to test whether a PP's membership in one of the two (at t_0) or three (at t_1) AI profiles can be used as a predictor of his or her behavioral intention. For each PP, the AI profile membership was used as a predictor (independent) variable. A dichotomous variable (1 = yes, 0 = no) was used to represent membership in the *AI-Educated* and *AI-Positive* profiles, while membership in the *AI-Unfamiliar* profile was used as the constant term in the regression equation (i.e., the base group against which the other two profiles were assessed). The behavioral intention measure, i.e., the PPs' intention to integrate AI in their future medical practice served as dependent variable.

With both the t_0 and t_1 data, we tested two regression models: model 1 only accounts for the AI profiles, whereas model 2 includes the three control variables, i.e., academic level, age, and gender as added predictors. Regression assumptions with regards to autocorrelation and multi-collinearity were confirmed with the variance inflation factor (VIF) and the Durbin-Watson test. At t_0, the regression results for model 1 (without the contextual variables) show that membership in the *AI-Positive* profile is significantly associated to a greater intent to integrate AI in medical practice. In model 2, the three control variables are found to provide no added explanation of the dependent variable, as membership in the *AI-Positive* profile remains the sole predictor. At t_1, the results for model 1 show that membership in the *AI-Educated* profile and membership in the *AI-Positive* profile are significant predictors of the PPs' behavioral intention with regard to AI, with the latter profile having the greatest influence. Again, in model 2, the three control variables had no additional influence on the dependent variable. Overall, membership in the *AI-Educated* and *AI-Positive* profiles explained 30% or more of the variance in the PPs' intention to integrate AI in their future practice. These results allow us to conclude that AI profiles, as derived in this study, may serve as powerful yet concise means of analysis and prediction when studying PPs' behavioral intention towards AI.

4. Discussion and Contribution

The principal finding of our study lies in providing a more nuanced understanding of the taxonomical profiles of prospective physicians with regard to their eventual adoption and use of AI. Specifically, following the first survey (t_0), two profiles were identified, one more *AI-Unfamiliar* and the other *AI-Positive*, the latter showing higher knowledge of and experience with AI, more positive attitudes toward AI, and greater intention to adopt AI in their future medical practice (see Tables 2a and 2b). Following the second survey (t_1), the two profiles were complemented by a third one, the *AI-Educated*. While the *AI-Unfamiliar* PPs remained the lowest on average in terms of knowledge, experience, attitudes, and intention, the *AI-Positive* PPs were characterized by more positive attitudes and greater intention, while *AI-Educated* PPs showed higher knowledge and experience on average, but a more moderate level of intention (see Tables 3a and 3b). These findings thus provide us with further knowledge of the interactions and effects of AI-related beliefs and attitudes, and they underline the potential value of configurational perspectives in this context.

Table 4: Regression analysis of the prospective physicians' AI profiles

dependent variable	Intention to integrate AI in medical practice			
	t_0 (n = 184) **T coefficient**		**t_1** (n = 138) **T coefficient**	
independent variables	model 1	model 2	model 1	model 2
AI-Unfamiliar profile (constant)	11.9***	0.9	4.8***	0.2
AI-Educated profile			2.5*	2.6*
AI-Positive profile	8.9***	8.7***	7.9***	7.9***
Academic level		0.1		0.1
Age		1.1		0.4
Gender		1.0		1.0
F	79.1***	20.2***	31.9***	12.9***
adjusted R^2	0.30	0.30	0.31	0.30

*: $p < 0.05$ ***: $p < 0.001$

Additional findings, found through a more extensive analysis of the AI profiles (see Table 4), allow us to conclude that having an *AI-Positive* profile is the best predictor of the PPs' behavioral intention with regard to AI, both in the pre- and peri-Covid-19 studies (t_0 and t_1). Moreover, in the latter study (t_1), we may conclude that having an *AI-Educated* profile is the second-best behavioral predictor. This further demonstrates that the configurational approach adopted here may serve as powerful, yet concise means of analysis and prediction when studying attitudes and behaviors toward digital health technologies in general, and AI-based technologies in particular. Remembering that our research was case-based rather than variable-based, and that we used AI profiles (or configurations) rather than individual variables as predictors of intention with regard to AI, the results presented here provide additional theoretical validity to the configurational approach (as opposed to the universalistic or "variance" approach). In other words, configurational theory and methods allowed us to delve more deeply into the relationships between individual beliefs, attitudes, and behavioral intentions toward the use of AI technologies in medical practice, and in so doing to better predict and explain such intentions.

Our study and its underlying configurational view thus provide an initial but potentially important contribution to medical informatics research by sensitizing researchers as well as medical educators and practitioners to the role of digital health technology profiles and "fit" related to the knowledge, attitudes, and intentions of prospective physicians with regard to these technologies, and to AI in particular (Zigurs & Khazanchi, 2008). Distinct profiles and associated causalities would require decisions in this context to be based on considerations of fit between the individual AI profiles, the associated educational measures, and intended outcomes in terms of individuals' intentions and behaviors with regard to the use of AI in medical practice (Rai & Selnes, 2019). For example, some medical students may be overly confident in the effectiveness of AI, while others may underestimate it or have ethical concerns (Barbour et al., 2019). These profiles may not be served well by identical curricular contents. In addition to educational measures, the significant differences between student profiles, from our view, also call for AI-related materials supporting informed student decisions related to the selection of their medical specialty. Especially if key variables, such as AI-related attitudes, are hard to change (Barbour et al., 2019), empowering students to self-select and better appreciate the future AI-related transformations in their specialty, would be preferable to less effective educational measures.

5. Limitations and Future Research

A limitation of this study lies in the sampled PPs' overall low level of experimentation with AI technologies. The lack of variance in this variable is such that it may be worthwhile to set future studies in other medical schools where, at the outset, digital health technologies and AI have a stronger presence in the curriculum. More evocative conclusions may also be drawn by sampling a greater proportion of medical students at the internship level.

Further insights may also be gained by analyzing emotional facets related to the role of AI in medical practices. In this regard, the concern of being replaced by AI was considered by prior research (Gong et al., 2019; Mehta et al., 2021; Park et al., 2021; Sit et al., 2020). Initial results suggest that exposure to AI tools and learning about their impact on medicine was associated with lesser anxiety related to the potential consequences of AI on the future profession (Gong et al., 2019; Park et al., 2021; Sit et al., 2020). Including such constructs in a configurational approach appears of value for future work aimed at examining antecedents of AI adoption.

In using cluster analysis as its research method, our study was meant to be exploratory in nature. While we identified configurations that were based on theoretically related causal conditions, we made no *a priori* assumptions as to the interrelationships and relative importance of these conditions in producing the outcome. Indeed, cluster analysis "is relatively ambiguous regarding the fine-grained differences among clustering variables and the configuration itself" (Payne et al., 2014, p. 125). Further confirmatory studies are thus needed, that is, studies that formulate and test theoretical propositions as to the precise nature of the configurations deemed to produce a high intention to integrate AI in medical practice. In this regard, second generation configurational analysis methods such as qualitative comparative analysis (QCA) would be appropriate (Fiss et al., 2013).

6. Conclusion

Our study uncovered distinct AI profiles, that is, patterns of beliefs and attitudes toward AI in medical practice that characterize medical students enrolled at a Canadian university. We also examined the association of these profiles with the sampled PPs' behavioral intention toward AI adoption. As a result, our exploratory study contributes to a better conceptual and empirical understanding of the role of AI-related knowledge and attitudes of prospective physicians. These insights hold implications for leaders in medical education on how to adopt, implement and orchestrate measures across areas such as curriculum design and delivery, experimentation-based training, as well as outreach and informing PPs with regard to career choices and expected requirements, thus allowing them to better prepare for the upcoming AI-induced transformation of medical practice.

7. References

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