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Front Pages

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The *Athens Journal of Health and Medical Sciences* (AJHMS) is an Open Access quarterly double-blind peer reviewed journal and considers papers from all areas of medicine (including health studies and nursing research). Many of the papers published in this journal have been presented at the various conferences sponsored by the Health & Medical Sciences Division of the Athens Institute for Education and Research (ATINER). All papers are subject to ATINER's Publication Ethical Policy and Statement.

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Athens Journal of Health and Medical Sciences

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The current issue is the second of the thirteenth volume of the *Athens Journal of Health and Medical Sciences (AJHMS)*, published by the Health & Medical Sciences Division of ATINER.

Gregory T. Papanikos
President
Athens Institute

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The Health Economics & Management Unit of Athens Institute will hold its **25th Annual International Conference on Health Economics, Management & Policy, 22-26 June 2026, Athens, Greece s**ponsored by the Athens Journal of Health and Medical Sciences. The aim of the conference is to bring together academics, researchers and professionals in health economics, management and policy. You may participate as stream leader, presenter of one paper, chair of a session or observer. Please submit a proposal using the form available (https://www.atiner.gr/2026/FORM-HEA.doc).

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- **Dr. Paul Contoyannis**, Head, Health Economics & Management Unit, Athens Institute & Associate Professor, McMaster University, Canada.
- **Dr. Vickie Hughes**, Director, Health & Medical Sciences Division, Athens Institute & Assistant Professor, School of Nursing, Johns Hopkins University, USA.

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- Acceptance of Abstract: 4 Weeks after Submission
- Submission of Paper: **DEADLINE CLOSED**

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- Abstract Submission: **6 October 2026**
- Acceptance of Abstract: 4 Weeks after Submission
- Submission of Paper: 5 **April 2027**

Academic Member Responsible for the Conference

- **Dr. Vickie Hughes**, Director, Health & Medical Sciences Research Division, Athens Institute & Assistant Professor, School of Nursing, Johns Hopkins University, USA.
- **Dr. Carol Anne Chamley**, Head, Nursing Research Unit & Associate Professor, School of Health and Social Care, London South Bank University UK.
- **Dr. Andriana Margariti**, Head, Medicine Research Unit, Athens Institute & Lecturer, Centre for Experimental Medicine, Queen's University Belfast, U.K.

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Is it Time for Canada to Institute Mandatory Labelling for Genetically Engineered foods? Assessing the Evidence

By Kurt Klein[*]*, Stavroula Malla*[±] *& David Forestell*[○]

More than 60 countries, including Japan, China and recently the United States, which are Canada's major trading partners, require mandatory labelling of genetically engineered (GE) food products. While Canada is a major producer and exporter of GE foods, Canada has only voluntary labelling requirements for them. This paper investigates the justification and possible effects of replacing Canada's voluntary labelling scheme with one that is mandatory. The paper sheds light on the important but neglected socio-economic policy issue of genetically engineered food labelling policy in Canada. It is shown that Canadian producers have been minimally affected by labelling regulations in export markets. In addition, it is shown that the cost of changing to a mandatory labelling requirement could be very substantial. Canada does experience some domestic pressure surrounding the labelling of these products, as a large proportion of Canadian consumers express a desire for more information. This 'right to know' demand is created largely by consumer advocacy groups, not the scientific or agricultural communities' influence on the public. With a clearer understanding of economic, social, political and regulatory factors that surround the labelling issue, several recommendations are made including increased public and private sector education about these genetically engineered food products, and no immediate need to change Canada's current voluntary labelling scheme. Conclusively, Canadian policy makers and market participants can feel confident in their current system but must remain vigilant to changes both domestically and abroad.

Keywords: *genetically engineered foods, voluntary labelling, mandatory labelling, public policy*

Introduction

Genetically modified or engineered foods (referred to hereafter as GE foods)[1] have been controversial in Canada from the time of their first appearance. All food products in Canada, including those that have been genetically engineered, are regulated jointly by Agriculture and Agri-food Canada, the Canadian Food Inspection Agency, Health Canada and the Public Health Agency of Canada (Government of Canada 2021). There is no requirement for labelling of GE food products in Canada unless a nutritional or compositional change has been made that

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[1]Genetic engineering (GE) and genetic modification (GM) are both used to describe recombinant DNA (rDNA) technology. GM is the term used in international agreements and in European regulation whereas GE is the term used in U.S. legislation (CBAN 2024).

poses a health or safety issue to consumers of the product (Canadian Food Inspection Agency 2015, Canadian Biotechnology Action Network 2023, Government of Canada 2024b, Government of Canada 2024d). Several consumer and environmental lobby groups (referred to hereafter as non-government organizations or NGOs) believe the Canadian government is falling short of its responsibilities and have challenged not only the safety of GE foods but also the amount and veracity of information that sellers of GE foods are required to divulge on the labels. These two opposing bodies have effectively defined the situation around GE foods as one of citizens' maximum welfare vs the consumers' 'right to know' (Smyth 2014).

The term *Frankenfood* was coined in 1992 by Paul Lewis, an English professor at Boston College (Mirchandani 2015). It was quickly picked up and used by some NGOs and highlighted in British tabloids in the early 1990s to describe GE food products. It was meant to create fear among consumers, to whip up hysteria, and to assert that these "unnatural" food products might be unsafe, unhealthy, and possibly environmentally destructive. Since the introduction of GE food products, debate has raged about the health risks and ethical implications of this new technology in plant and animal breeding. Many influential NGOs have continued to protest the introduction and availability of GE foods and want them to be banned from sale or, if not banned, labelled to contain the scary term of "contains GEs or GMOs" to dissuade consumers from purchasing the products.

Since all food products offered for sale in Canada have been subjected to a strict testing and regulatory regime prior to being offered for sale, most scientists and scientific associations generally have supported the existing voluntary labelling scheme (Government of Canada 2021, 2024b). Further imposed information requirements in the form of mandatory labelling, they contend, would impose additional costs that inevitably would be passed onto consumers, agricultural growers, and secondary producers without enhancing the safety or quality of the food products (Bovay and Alston 2018). Additionally, Canadian taxpayers might also incur increased tax requirements or opportunity costs of alternative uses of government resources to support the regulative and legislative efforts required to establish, maintain, and enforce a new system (Roe et al. 2014).

However, recent mandatory labelling requirements for GE foods in the United States, a major market for Canadian-grown GE canola and soybeans, might pose significant challenges for future agricultural trade. This policy makes the U.S. the 65th country with a mandatory GE labeling policy. Labelling regulations that differ across borders can create significant trade barriers and additional costs for producers.

In this paper, we consider the case for mandatory labelling of GE foods in Canada. The goal is to gain sufficient insight into the issues surrounding GE labelling so that useful policy recommendations can be made in the current environment of conflicting views and disparate public and private agendas. The economic consequences of the new U.S. and other countries' mandatory GE labelling laws for Canada, as well as the economic consequences, i.e., the potential benefits and costs associated with mandatory labelling of GE foods in Canada, have not been adequately examined in the academic literature. To date, no scientifically credible study of potential costs that would be incurred by a change to a mandatory labelling scheme has been conducted in Canada (though they're likely to be substantial), and

there is evidence that suggests many Canadian consumers would prefer mandatory labelling of GE food products (The Strategic Counsel 2016). Therefore, understanding the United States labelling system, recently changed to mandatory for all GE products and in a market culture not dissimilar to Canada's, provides an opportunity with which to gain understanding into the possible effects if Canadian authorities were to impose a mandatory labelling scheme for GE foods in Canada.

What are Genetically Engineered Foods?

Traditionally, domestication and improvement of plants and animals involved repeated crossbreeding and selection of offspring throughout several generations for specific desired traits that improved yields, resistance to pests, quality or other desired characteristics. If successful, the improved plant or animal would exhibit the improved trait(s) in successive generations. This was a time-consuming and not always successful process. In the case of Canadian wheat, the process could take 12-15 years with successive generations grown in Canada during the months May – September, followed by planting seeds from the Canadian harvest in the southern hemisphere (often in Chile) to grow another generation during the months of October to March (Klein et al. 1996).

In recent years, with improved scientific knowledge and computer technology, scientists have been able to isolate specific genes of interest, insert those genes in a plasmid to multiply the genetic material, move the plasmid into a plant or animal cell, and insert that DNA into the plant or animal chromosome – all within a laboratory (e.g., Gray and Malla 2001, Malla and Gray 2003, 2005, Brewin and Malla 2012, 2013, Malla and Brewin 2015, 2019). The process greatly hastens the development of improved plants and animals compared to the traditional approach of growing multiple successive generations after crossbreeding and selection.

The first GE animals (mice) were produced in 1982; the first GE plants were produced in 1985 (e.g., Gray and Malla 2001, Brewin and Malla 2013, 2014). Regulations in the United States for the deliberate release of GE plants were released in 1993. The first GE tomato (trade-named Flavr Savr) was approved for sale in the United States in 1994. It was developed to remain firm after harvest and therefore could remain on the vine longer prior to shipment. This allowed producers increased flexibility in the timing of harvest and movement of product.

Canadian authorities approved the first GE crop (canola) in 1995 (Brewin and Malla 2012, Malla and Brewin, 2015, 2019). Since GE corn, flax, sugar beets and soybeans have been approved for production in Canada (CBAN 2024). In 2003, international agencies developed international guidelines and standards by which national bodies could determine the safety of GE food products. The Organization for Economic Co-operation and Development (OECD), World Health Organization (WHO), and Food and Agriculture Organization of the United Nations (FAO), under the Codex Alimentarius Commission (Codex Alimentarius 2023), agreed that if any GE crop or food composition was the same, or similar, to that of non-engineered crops that had a history of safe use for feed and food, except for the expressly modified differences, the GE crop would be considered 'as safe as' the non-modified

crops (Delaney et. al. 2018). Therefore, food products that are "as safe as" the non-GE equivalent should need no special identification on the label, which, by itself, might frighten consumers needlessly.

In 2003, the Cartagena Protocol on Biosafety extended this convention and ensured that people dealing with GEs conducted health and safety tests on their products. In 2018, the Nagoya-Kuala Lumpur protocol developed a framework for handling liability in case GE products caused harm. Adoption by farm producers of GE plants was rapid. The worldwide area planted to GE crops increased from 1.7 million hectares in 1996 to 206 million hectares in 2023 (Agroinvestor 2024). In Canada, 100% of sugar beets and over 92% of canola, corn and soybeans plantings were GE cultivars in 2023 (Statista 2024).

What are Some Benefits of Genetically Engineered Foods?

In addition to greatly decreasing the time required for breeding improved cultivars, first generation GE crops have enhanced input traits such as herbicide tolerance (that result in greater yields with less herbicide applied), greater insect resistance, and better tolerance to environmental stresses (Malla and Brewin 2015, 2019, Malla and Klein 2025). The GE crops are not significantly different from traditionally grown crops in appearance, taste or nutrition. Where approved, farmers rapidly adopted these GE crops due to increased profitability from higher yields and generally reduced input costs. Also, the planting of first-generation GE crops had a positive environmental result due to the need for a lower amount of less toxic herbicides to achieve adequate weed control (Phillips 2003).

A second generation of GE crops has offered many benefits to consumers, including healthier fats, increased levels of proteins and/or specific amino acids, modified carbohydrates, increased micronutrients, increased flavours, and more (Malla and Brewin 2015 2019, Malla and Klein 2025).

In Canada, where GE food products have been approved for sale for more than two decades, commercial grocery stores are full of products that include GE content. Food products marketed by major brands, including Kellogg's, Kraft, General Mills, Nestle, Coca Cola, Quaker, Uncle Ben's, Orville Redenbacher, Johnson & Johnson, P & G, Campbell's, and dozens of others are prominent in grocery stores in Canada. Indeed, a Canadian shopper walking the aisles in a major grocery store in Canada would have a hard time avoiding the purchase of any product that was not genetically engineered.

The Issue

Mandatory labelling requirements for GE foods, recently imposed in the United States and in effect in 64 other countries, might pose significant challenges for future exports of Canadian grown bioengineered crops. Canada has become a major producer and exporter of GE crops and different labelling regulations among trading partners potentially can create trade barriers and/or diminished market opportunities.

Prior to July 2016, voluntary labelling of GE (as well as non-GE foods) was acceptable in the U.S., as is the case in Canada. Following a phase-in period, since 2022, food products marketed in the U.S. that contain GE ingredients are required by federal law to indicate that fact on the labels (Canadian Biotechnology Action Network 2023).

In Canada, the labelling of GE ingredients in food products continues to be voluntary. However, all food products offered for sale (including those with GE content) undergo a rigorous assessment to ensure that toxic or allergenic compounds are not present and there is no evidence of negative human health effects in the GE product (Government of Canada 2024c, Government of Canada 2024d).

To promote greater adoption of voluntary labelling of GE content in food products, the federal government participated in developing national standards to provide guidance and increase the application of labels. In 2021, the Standards Council of Canada (SCC) officially adopted a recommendation of the Canadian General Standards Board (CGSB) regarding the advertising and voluntary labelling of foods that are, and are not, products of genetic engineering (Government of Canada 2024c). However, as noted by Bain and Dandachi (2014), there are obvious shortcomings of voluntary labelling, including inconsistent application of labels, non-enforceability of labelling and, of course, the direct costs associated with a program that has few guarantees of informing the Canadian public of their specific concerns about the safety and healthfulness of purchasing and consuming GE foods.

The process by which GE crops are tested in Canada is robust. A combination of growing and environmental conditions that ensure a significantly varied outcome, broad samples of non-bio-engineered varieties against which to test extant traits, and statistical modelling that result in intervals derived from cumulative historical composition data are factors used to measure GE crop safety (Ridley et al. 2002, Hong et al. 2014). As GE crops are not always intended for direct human consumption but as feed for livestock, extensive tests are also conducted to verify their safety to livestock directly and by extension for human consumption.

While voluntary labels have the potential to partially defuse the GE labelling debate, they are unlikely to fundamentally address the social concerns of the anti-GE movement.

The Anti-GE Movement and Consumers' Right to Know

Consumer and environmental lobby groups (usually NGOs) have campaigned strongly against GE ingredients in food products since their first appearance. They have railed against perceptions of food safety issues despite assertions by the scientific community of no evidence of adverse health or environmental impacts from the consumption of tested and approved GE food products (FAO 2002). Demands for mandatory labelling of GE foods because consumers have the right to know what they purchase and eat have been a persistent request of the anti-GE movement (Hobbs and Kerr 2006).

Numerous examples of food scares that were unrelated to GE ingredients in food products have been exploited by groups that are strongly opposed to GE ingredients in food products. Among many examples, Xiao and Kerr (2022) recount

how the eating of (what turned out to be) non-GE corn led to reduced sperm counts in Chinese college students, and suggestions that eating GE soybeans could cause tumours and infertility.

Maeseele (2014) stated that some NGOs can be classified as 'alternative science communicators' in the manufactured social conflict regarding agricultural biotechnology. This conflict arises from a social movement that uses counter-scientifically supported facts to critique the currently accepted science and technology. The critique itself is a result of the commercialisation of science, uniting economic interests in the condemnation of biotechnology and the irregular standards surrounding scientific communication. Much public relations and corporate interest-based communication seek to provide 'alternative facts.' Once institutional science communication is indistinguishable from corporate communication, NGOs can challenge scientific knowledge by instigating suspicions of recognized scientific practices and the social values supporting those scientific endeavours.

As Pham and Mandel (2019) note, anti-GE food NGOs often pursue private politics, circumventing traditional governmental institutions, to gain direct influence over entrepreneurial companies that produce GE food products. These NGOs then endeavor to obfuscate any evidence establishing the safety and long-term beneficial impact of this new technology. This allows the NGO, a non-scientific organization, using technical language, to contest existing scientific literature with the presumed validity of regulated scientific communities. The NGOs' 'advantage' is the lack of necessity for peer review, and the non-conformity allowed through their communication approaches. As noted by Hameleers and Van der Meer (2021), the net effect is a uniform distrust of scientific communication and the redirection of scrutiny towards the scientific organizations and their methods as opposed to examination of the facts that those institutions present. Although all major countries have extensive regulations concerning the safety and healthfulness of GE food products, a formidable "right to know" movement, based on possible human health and environmental risks, has been the focus of numerous NGOs that have an anti-GE agenda (Peterson et al. 2000, Breckling et al. 2011).

What do Canadian Consumers Want?

There have been attempts, both governmental and academic, to understand the relationship Canadian consumers have with GE foods. In a report submitted to and adopted by Health Canada, the Strategic Counsel found that "(Canadian) consumers' understanding and impressions of GE foods could be described as not that well-formed, as demonstrated by the lack of detailed knowledge…" (The Strategic Counsel 2016, 4)[2]. In the same report, the Strategic Counsel indicates that negatively biased media coverage in conjunction with anti-GE activities by NGOs have largely shaped public opinion. Their report was based on a cross-country survey in 2018 of

[2]"Not that well-formed…" in the quote from the Strategic Counsel refers to the opinions held by the surveyed public and seem to be based on a low understanding of food science and technology. The low level of scientific literacy extends to agricultural practices, market implications of technology, and quantitative consequences of consumer preferences. Negative or conflicting views can be attributed to messaging from anti-GMO advocates and environmental groups (The Strategic Counsel 2016).

consumers who were 19 years of age and older in Toronto, Vancouver, Saskatoon, Halifax, and Quebec City.

The Strategic Council report indicates that up to 78% of consumers did not believe the voluntary labelling scheme employed in Canada was sufficient or credible and they would be in favour of a mandatory labelling requirement. This is understood to be primarily an emotional response and indicates a significant gap between scientific communication and acceptance of scientific facts. Further, if mandatory labelling of GE food products were instituted, the increased "transparency" and enhanced ability to make "informed decisions" likely would result in 62% of surveyed consumers actively avoiding GE-labeled food (The Strategic Counsel 2016, 39).

Academic findings of the Canadian consumer response to GE foods and labelling have been mixed. A study conducted by Baynham (2018) in which 22 types of a standardized food product - all having the same price – had its labels modified into 5 distinct categories: (1) control (no label or might contain GE ingredients label); (2) GE label: might contain GE ingredients; (3) GE label: might contain genetically modified ingredients; (4) non-GE or GMO label; and (5) organic label: Canada Organic. All items were randomly assigned labelling so as not to incur existing preference bias to the 165 individuals in the survey. Impacts of the labels were measured by eye-tracking technology of a group primarily consisting of participants between the ages of 20 and 37 years old. The study found that the average consumer might not know what information labels precisely communicate but those with a 'non-GE' label received the most attention.

An alternate cross-country Canadian survey of consumers conducted by Charlebois et al. (2018) found further evidence that indicated a mixed response to mandatory GE food labelling. The study had a sample size of 1046 participants and was held over a 3-day period in May 2018 in Quebec, British Columbia, Atlantic Canada, Ontario, and the Prairies. The aim of the study was to measure Canadian attitudes towards GE foods and assess the confidence in Canada's voluntary labelling scheme. This study informed the respondents, in uncomplicated terms, about genetic engineering and testing standards in Canada before the survey was undertaken. After a base knowledge was achieved, the study asked the participants to complete a survey that took an average of 2 minutes to complete. The study found that Canadian participants believed GEs to be safe, unsafe, and unknowingly safe in almost equal proportions. Further, the result that 44% of the participants believed that the health effects of GEs were not clearly understood directly conflicted with 56.3% who believed that the current level of GE testing was sufficient. The study also found that approximately 88% of all surveyed Canadians would passively support mandatory GE content labelling. Simultaneously, these same participants indicated that the price of the product was almost 3 times more important than knowledge of the item to be purchased, having GE ingredients.

The consumers' "right to know" is established and upheld in Canada by the federal government and is facilitated directly by the Office of Consumer Affairs (OCA). In conjunction with the federal government's commitment to transparency, a policy of "open data, open information and open dialogue" is employed, and the OCA oversees the legislation administered by the Canadian Food Inspection Agency (CFIA) (Government of Canada 2024a). This agency is tasked with providing

standards, in conjunction with the Canadian *Food and Drugs Act*, that establish food labelling policies with respect to health and safety. Regarding GE products, CFIA can mandate specific label requirements where the health and safety of consumers might be affected (Government of Canada 2024b).

While it is obvious that people want to know if the food they consume is safe, nutritious and healthy, despite overwhelming evidence to the contrary, there exists a persistent belief that GE foods pose a substantial threat to human health and the safety of the environment (Charlebois et al. 2018).

In a more recent study by Statista (2024), Canadians 18 years and older were asked to state their opinions on the safety of GE foods. Out of 1046 respondents, 37.7% agreed that GE foods are safe to eat, 34.7% disagreed, and 27.6% were unsure.

In another survey, Shahbandeh (2024) found a higher percentage of respondents in the main Canadian food producing provinces of Saskatchewan (60%), Alberta (54%), Manitoba (48%) and Ontario (43%) considered GE foods to be safe. However, almost half of the respondents in Atlantic Canada were unsure about the safety of GE foods. Many consumers reported they are wary of potential risks like the introduction of toxic compounds and/or allergenic compounds in their food products

The mixed response by Canadian consumers, even when uniformly informed about the testing and safety of GE foods, presents a distinct problem for regulatory authorities in the Canadian government. While most participants seem willing to passively support a switch from voluntary to mandatory labelling, there is distinctly insufficient knowledge held by participants about health and environmental effects that should be the foundation of such a change. Further, the importance of such GE information is undermined due to the relative position it has when compared to the convenience and price of foods that might, or might not, contain GE ingredients. Even if the current voluntary labelling system has been deemed sufficient by Health Canada, Office of Consumer Affairs (OCA), and the Canadian Food Inspection Agency (CFIA), there is obvious confusion and mistrust of GE foods among Canadian consumers. New legislation, including adjusted labelling schemes and education initiatives, would have to overcome any misinformed or under-informed bias held by the consumers to whom they are accountable.

Mandatory Labelling of GE Food Products – 65 Countries Require it

Sixty-five countries, many of which engage in trade of food products with Canada, now require some form of mandatory labelling of GE food products, arguing that consumers have the 'right to know' (Wohlers 2013). The European Union (EU) is known for its stringent regulations on GEs, following the precautionary principle. All food products that contain more than 0.9% of authorized GEs must be labelled as such in EU countries.

According to Kalaitzandonakes and Bijman (2003), the EU's labelling policy, established in 1997, set the precedent for the first broad rejection of GE products by legislators and retailers. The EU's rejection of GE products was founded on an

extreme version of the precautionary principle[3]. The GE labelling requirement caused EU retailers to assume that these products would be unwelcome by most of their consumers. As retailers in the perishable foods industry typically do not want to carry inventory that experiences little or no turnover, the default position was to *not* acquire products manufactured or labelled with GE content. Hence, the rejection was not by consumer choice but by an absence of choice.

Mexico, China, Japan, the United States and other important markets for Canadian agricultural and food products require that GE foods be labelled as such. The recently imposed U.S. federal law on mandatory labelling of GE foods was justified as providing greater transparency and supplying consumers with increased access to information about their food (USFDA 2016, 1). Certain provisions within the recent U.S. law illustrate the level of complexity that is involved in mandating the labelling of GE foods:

- Food from an animal cannot be declared bioengineered on the basis that animal has been fed bioengineered food.
- The minimum amount of bioengineered food present in food needs to be defined by the USDA to carry the bioengineered label.
- The disclosure of bioengineered food can be a text, a symbol, or a digital or electronic link according to the discretion of the food manufacturer.
- USDA is asked to conduct a study to see whether challenges exist in regard to access to electronic information.
- In certain cases, a telephone number or internet site are allowed as a means of disclosure.
- Restaurant food and "very small" food manufacturers are excluded from disclosure requirements.
- States (and its subunits) are prohibited from establishing or continuing to require other GMO labeling practices.
- Food cannot be claimed to have no bioengineered food when there is no disclosure label.
- Certification by USDA's National Organic Program "is sufficient" for a claim that bioengineered food is absent.

Should Canada Require Mandatory Labelling of GE Food Products?

In conjunction with the strong preference of agri-food producers, the Canadian government has maintained a voluntary labelling scheme of GE food products sold in Canada (Government of Canada 2024b). A collection of governmental agencies has shown that the current voluntary labelling scheme is cost effective, scientifically rigorous, and reliable (Government of Canada 2021, 2024b).

[3]The precautionary principle is a decision-making paradigm with four central components: engaging in preventive action in the face of 'uncertainty'; allocating the 'burden of proof' to the proponents of a possibly harmful activity; creating alternatives to possibly harmful actions; and increasing public participation in decision making (Kriebel et al. 2001).

In contrast to Canada's voluntary labelling scheme, mandatory labelling requirements are currently in place in 65 countries, several of which Canada conducts significant trade with. However, despite Canadian producers having very limited or no access to markets in the EU, there have been few negative long-term trade consequences to the Canadian agricultural industry from the mandated labelling requirements of GE food products in major importing countries of Canada's GE commodities. Indeed, as Canada's production and yield of GE canola has increased, so have Canadian canola exports to the U.S., China and Japan (CCC 2024a, b). While there is some protectionism surrounding Chinese domestically developed and grown GE crops, shortages in their own raw and refined products are still imported from Canada (Liang et al. 2022).

Since the full implementation of the National Bioengineered Food Disclosure Standard (NBFDS) in the United States on January 1, 2022, there has been very little impact to Canada's trade in GE canola with that country. Canola oil is basically stripped of its DNA when refined for food use. Despite Canadian canola being genetically engineered, the product derived from GE canola does not necessarily qualify for mandatory disclosure (USDA, 2024). The USDA *does* require bioengineered ingredients to be disclosed, but not if the genetic material is undetectable. Further the NBFDS states that "Food from an animal cannot be declared bioengineered on the basis of that animal having been fed bioengineered food." (U.S. Congress 2016a).

Most of the corn, canola, soybeans and sugar beets harvested in the U.S. are genetically engineered and approved for human and animal food consumption. For example, high fructose corn syrup made from GE corn is a major sweetener that replaces sugar in a wide variety of approved food and drink products. Corn oil, canola oil and sugar from sugar beets are stripped of the DNA in them. The USDA requires bioengineered ingredients to be disclosed, but not if the modified genetic material is undetectable (Adalja et al. 2022)

According to the Canola Council of Canada (2024b), secondary markets in China, Mexico, Japan, and the United Arab Emirates were among the largest importers of Canadian GE canola in 2023. These countries all have their own safety and regulatory guidelines surrounding GE products. However, there is no evidence that labelling requirements in these countries contributed to the decline in imports of Canadian-produced GE commodities.

Japan, which has some of the strictest regulations involving imports of GE food products, continues to allow the importation of Canadian canola and its refined products. Early in 2023, the Japanese Consumer Affairs Agency (CAA) updated their agricultural product list that requires mandatory GE labelling. Canola is one of the 9 major crops that has been exempted from the mandatory labelling requirement and Canadian GE canola continues to be imported and sold in Japan as that country currently does not grow any of its own (Neo 2023).

Gruère (2007) noted that countries that use voluntary labelling of GE foods provide consumers with a choice of food products with and without GE content. On the other hand, while mandatory labelling of food products is meant to provide consumer information and consumer choice, in most countries with mandatory labelling requirements (notably those in the EU), only non-GE, non-labelled foods are available. Mandatory labelling has resulted in food processors and retailers removing

any GE ingredients (many of which would enhance nutrition and/or flavour) to avoid protests by anti-GE activists.

What is Known about Costs for Canada to Mandate Labels on GE Foods?

The call for more transparency surrounding labelling of GE foods in Canada can be regarded as social and political pressure and not really a way to accurately represent scientific facts on healthfulness and safety of approved GE food products. Food processors might respond to imposed mandatory labelling by replacing those GE ingredients with non-GE ingredients produced using conventional technology or with organic ingredients. Non-GE replacements that yield less and have lower nutritional content would impose extra costs, ultimately an extra burden on the consumer.

The legislative processes required to coordinate, institute, mandate and monitor a new labelling system are substantively difficult and costly. They require concerted effort for an extended length of time.

Lesser and Lynch (2014) noted that private costs of implementing a mandated labelling scheme include the costs of segregating GE foods from non-GE foods, keeping each separate during the entire production chain to the placement of finished products on store shelves. The segregation requires additional warehousing, retail, manpower, and operating space. Additional labour would be needed for documentation, identity preservation of both GE and non-GE products. Private (or possibly public) costs would be required for enforcement agencies that check and maintain segregation standards, and agencies that design, regulate, and verify the final labelling standard. Then, there would be costs for the labels themselves (with descriptions in two official languages).

While no definitive studies have been conducted on what a mandatory labelling requirement for GE foods in Canada would cost, a detailed cost analysis for the United States labelling scheme conducted by Bovay and Alston (2018) provides some guidance on the possible magnitude of costs that would be incurred if Canada were to follow the United States path. Bovay and Alston (2018) based their study on previous investigations by noted economists Alston and Sumner (2012), Shepherd-Bailey (2012), Lesser and Lynch (2014), and Dunham (2016).

They estimated the cost for labelling alone would be in the neighbourhood of USD 6.1 billion, with additional costs for warehouse and retail space, segregation, certification, and monitoring of at least USD 7.1 billion per year. By scaling Bovay's and Alston's (2018) estimates to Canada's population relative to that in the United States and their cost estimates to 2024 Canadian dollars (including inflation experienced since the Bovay and Alston study), the costs of imposing a mandatory labelling scheme for GE food products in Canada would likely be close to CAD 1 billion for labelling alone and at least another CAD 1 billion for all other costs associated with a change in labelling scheme annually (Authors Scaled Calculation based on Bovay and Alston 2018, Trading Economics 2024a, Trading Economics 2024b, Bank of Canada 2024).[4]

[4]The formula used was: ([k x Pv]/ratio) where: k equals scaled calculated costs in USD in 2012-2016; Pv is the proportional value derived from A x Var. (where: A is the compounded rate of inflation, calculated annually for 10 years at an average annual rate of inflation for Canada of 2.2% (similar to US average annual rate of inflation of 2.1%) and Var. is the variance in exchange rate between USD and CAD

Overall Assessment and Policy Recommendations

While 65 countries (including Canada's major trading partners) have mandatory labelling laws for GE foods and food products, Canada's agricultural and food producers have not (so far) experienced major disruptions when exporting GE commodities to these countries. While many Canadian consumers claim (in surveys) to prefer that GE foods be required to be labelled as such, there have been no widespread protests or campaigns in Canada to "encourage" the federal government to make labelling of GE food products mandatory. Indeed, the widespread availability of GE food products on grocery store shelves throughout Canada (as readily observed in shopping baskets) suggests a lack of urgency to change the current voluntary labelling system.

Costs of changing to a mandatory labelling requirement, though unknown in detail, would likely be excessive relative to the benefits obtained. The present voluntary labelling scheme continues to serve Canada's food industry well and allows consumers to have a wide choice of GE and non-GE food products available that have been subjected to Canada's highly regarded food inspection and approval process.

The voluntary labelling scheme, as it exists in its present form, has proven itself sufficient with regard to the safety of food products in general. And there is no scientific evidence to suggest that Canadian approved GE food products warrant any further special attention. However, it is incumbent for agencies within the government that create and monitor such policies to remain vigilant with regards to new information and concerns about GE foods and food labelling.

Finally, Gruère (2007) presented eight critical questions that should be asked before Canada (or any other country) thinks about introducing a mandatory regulatory system for GE Food products. They are listed below.

1) Is GM labeling necessary and if so for what reason?
2) Is it genuinely demanded by a majority of consumers and considered a labeling priority?
3) If labeling is requested, what type of GM labeling approach will best fulfill its objective?
4) What will be the reaction of the food industry to labeling, and will it result in consumer choice?
5) What should be the labeling content, what are the coverage and the threshold of labeling?
6) How will implementation be done and at what costs?
7) Would the chosen labeling have any effect on the potential use of GM crop technology?
8) Would it be compatible with the country's general economic goals and its international obligations?

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between January 2014 and December 2023 of +5.7% CAD); and ratio is the average historical U.S. population on January 2014 compared to the current Canadian population in December 2023.

Conclusion

The regulation of all food products in Canada, including GEs, is undertaken jointly by Agriculture and Agri-food Canada, the Canadian Food Inspection Agency, Health Canada and the Public Health Agency of Canada (Government of Canada, 2024c). Economists and other members of regulatory bodies within the Government of Canada continue to express their support for the existing voluntary labelling scheme for GEs (Government of Canada 2024b). While a large proportion of Canadian citizens claim in consumer surveys to not trust either GE products or the Canadian Government (The Strategic Counsel 2016), there's little evidence of Canadian consumers shunning the wide availability of GE food products on Canadian grocery shelves. Indeed, food products that contain GE corn, canola, and soy ingredients in processed foods are pervasive in Canada's existing food supply. Charlebois et al (2018) estimated that more than 75 per cent of all food products sold in Canada contain at least one GM ingredient.

However, mandatory labelling policies are currently in place in 65 other countries, including China, Japan, and recently the United States - countries with which Canada conducts significant trade. In examining the evidence for and against changing the voluntary GE labelling in Canada to a mandatory requirement, it was noted that NGOs and consumer advocacy groups have an outsized influence on the perceptions commonly held by Canadian citizens (Peterson et al. 2000). While many Canadian consumers report a lack of trust in GE food products under Canada's voluntary GE labelling scheme, the recent change in the United States from a voluntary to a mandatory labelling scheme resulted in little to no economic benefit but, likely, a significant on-going cost, according to Bovay and Alston (2018). Also, it was noted that Canadian producers have been only minimally affected by mandatory labelling regulations in export markets. As the Canadian government is arguably maintaining a high standard of safety and accountability for consumers, periodic reassessment of labelling practices for GE foods and ingredients can plausibly increase social welfare and individual well-being. The Canadian government seems to understand that there is presently no additional benefit in creating, implementing and administering a new mandatory labelling system. While a change to mandatory labelling might be beneficial to Canada in the future, the most reasonable course of action (and our recommendation) is to 'wait and see'.

Despite the relative lack of understanding and belief in governmental testing, approval and regulatory procedures, consumer confidence is a key element in a smoothly working market economy. A reasonable way to combat erroneous beliefs is education. Backing up the voluntary labeling scheme with increased and sustained public education around the safety of approved and regulated GE food products will expand consumer awareness and, possibly, reduce social and environmental concerns. Improving consumer confidence in the voluntary Canadian labelling scheme can be accomplished by making the process more transparent at the provincial and federal levels. Lastly, educating Canadian citizens and consumers on the structure, role and influence of NGOs might help to mitigate the amount of influence these organizations have over government regulations and public opinion.

A final recommendation entails the implementation of recurring governmental assessments regarding the voluntary GE labelling regime. Engaging representative consumer organizations in these reviews could strengthen public trust in both the regulatory oversight and the overall safety of GE products. Routine evaluations would allow the government to identify and address emerging domestic or international concerns. This proactive approach ensures the system remains relevant without incurring the unnecessary costs associated with premature or illogical changes.

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Risk Management for Smart Healthcare System: A Hybrid MCDM Framework

*By Abdullah Ali Salamai**

Smart healthcare management systems (SHMS) play a vital role in medical centers. SHMS has various risks and threats that affect patient care. So, risk management is the best choice to identify and mitigate these risks. This study proposed a multi-criteria decision-making (MCDM) framework for identifying risks in SHMS and selecting the best project in SHMS to reduce risks. This study used the MCDM method to deal with conflict criteria. There are two MCDM methods: CRiteria Importance Through Intercriteria Correlation (CRITIC) and Additive Ration Assessment (ARAS). The CRITIC approach is used to compute the criteria weights, and the ARAS algorithm is used to select the appropriate projects in SHMS. The neutrosophic set (NS) was applied with MCDM methods to deal with inconsistent data in the evaluation process. The results show the Health Data Informational System project is the best. Sensitivity analysis was conducted to show the stability of the rank. The comparative study was conducted to show the effectiveness of the proposed methodology. The outcomes demonstrate the rank of projects is stable through all scenarios, and the proposed methodology is effective compared with others MCDM methods.

Keywords: *risk management, portfolio management, smart healthcare, neutrosophic set, MCDM*

Introduction

The increasing population worldwide faces the development of recent technologies in medical centers and healthcare organizations. People need demands of medical care and a better quality of life (Yang et al. 2020). So, medical centers and healthcare systems are essential to provide solutions for improving patient care. Various medical centers have developed smart healthcare management systems (SHMS) to aid them in medical processes, operations, and healthcare assignments and activities. SHMS has multiple risks faced by various resources. So, risk management is used to identify and reduce these risks (Yang et al. 2022). So, choosing the greatest SHMS is a decision-making issue. This problem has various criteria and alternatives.

Fuzzy set (FS) deals with uncertainty and vague information. The intuitionistic fuzzy set (IFS) generalizes FS as membership and non-membership degrees. IFS cannot deal with indeterminate information and only deals with ambiguous data. The neutrosophic set (NS) was generalized with three degrees: truth, indeterminacy, and falsity membership degrees (Broumi et al. 2018, Wang et al. 2010). NS is a generalization of classical fuzzy set and their extensions. Ns were applied in various decision-making problems like transportation systems (Nabeeh 2023), evaluating

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students' performance (Adebisi & Broumi 2024), heart disease (El-Douh et al. 2023a), evaluating the quality of suppliers (Sallam & Mohamed 2023), and evaluating health sustainability (El-Douh et al. 2023b).

The single-valued neutrosophic sets (SVNSs) are a subset of NS that deal with vague and uncertain information. SVNSs are integrated with a multi-criteria decision-making method to overcome uncertain information. MCDM deals with conflicting criteria (Aruldoss et al. 2013).

The CRiteria Importance Through Intercriteria Correlation (CRITIC) approach was applied to obtain the weights of the criteria. the feature weights are obtained by applying a decision matrix instead of a pairwise comparison matrix. The CRITIC method is applied to decision-making problems. The CRITIC method has various benefits such as no need for independence of criteria and qualitative criteria can be converted to quantitative criteria (Alinezhad & Khalili 2019).

The Additive Ration Assessment (ARAS) method was introduced in 2010 as an MCDM algorithm to show the greatest alternatives from various projects. The ARAS algorithm was applied to decision-making problems to rank the projects. The ARAS algorithm ranks the alternatives based on the utility degree of every alternative. The ARAS method has various benefits: it is the compensatory method, converts the qualitative criteria into quantitative criteria, and the criteria are independent (Liu & Xu 2021).

This study proposed a decision-making methodology for risk management in the healthcare system by identifying criteria and alternatives. The CRITIC method is used to obtain criteria weights. The ARAS approach is applied to rank the other options. The neutrosophic set integrated with MCDM methods to overcome uncertainty in the evaluation process.

Risk Management

Risk management is the process of controlling and managing risks by performing some criteria like identifying, evaluating, and controlling risks. Risks in systems and organizations come from various sources like financial uncertainties, strategic risks, and technology risks. Risk management can identify the relationship between various elements of systems and organizations and show effects on systems goals. Risk management aims to minimize the risks and preserve the safety and value of the system by making a smart system (Akindote et al. 2024).

The healthcare system faces various risks that affect system performance and patient health. Risk management can control risks to improve patient care. Patient information can be attacked by attackers across all systems. Hence, this information must be preserved and maintained. The risks of patients in healthcare systems can be controlled by risk management healthcare. Risk management can be developed, implemented, and processed to address risks in healthcare to reduce and overcome these risks. Healthcare staff and managers must cooperate to face the risks in healthcare to provide risk management (Niv & Tal 2024).

Risk management in healthcare can identify, evaluate, and minimize the risks to patients, visitors, staff, and organizational assets. Risk management in healthcare can control and mitigate risks through various staff, such as healthcare practitioners,

and cybersecurity systems to protect health data. Risk management in healthcare systems aims to identify potential risks and take all necessary measures to reduce and mitigate them.

There are five basic steps in risk management in healthcare systems: establishing context, identifying, analyzing, evaluating, and managing risks. In this study, we identify some of the risks in healthcare systems: threats and patient care. Then, we analyze and evaluate these risks using MCDM methods to show the highest and most minor importance. Then, these risks are reduced by developing four projects and selecting the best one to minimize these risks.

Portfolio Management

Portfolio management chooses, ranks, and controls programs and projects for organizations and systems using strategic objectives. Portfolio management aims to show the strengths, weaknesses, opportunities, and risks and how to develop a project to overcome these risks. There are various strategic management programs and projects in healthcare systems to obtain all objects. Portfolio management can aid in ranking projects in healthcare systems to show their goals and impacts, increase and improve the value of projects and programs, and how these projects affect patient care (Elsayed et al. 2024, Odeyemi et al. 2024).

Implementing Portfolio management in healthcare systems and organizations can improve the system's ability to obtain patient care and improve management effectiveness. The projects and programs can enhance patient care in the healthcare system. This study developed four projects in Portfolio management to show the best project to reduce risks in healthcare systems and improve safety and patient care.

Contributions of this Study

The contributions are:

- This study proposed a framework for risk management in healthcare systems and portfolio management.
- This study meticulously identifies a comprehensive set of risks in healthcare and evaluates them using the rigorous MCDM methods, specifically the CRITIC method for computing the weights of criteria.
- This study identifies a set of projects in healthcare to minimize the risk in healthcare by applying MCDM to select the best project to reduce risks. The ARAS method ranks the alternatives (projects) and selects the best project.
- This study used the NS to deal with the uncertainty in assessment criteria and alternatives. The neutrosophic set is integrated with MCDM methods like CRITIC and ARAS.
- The sensitivity and comparative analysis were performed in this work. A sensitivity analysis was performed to display the stability of the ranking of alternatives. The comparative analysis shows the effectiveness of the proposed methods compared with other MCDM methods

Literature Review

This section shows the previous studies on risk management in healthcare systems. Healthcare systems are affected by the innovative and recent technology to select the best quality care in complex systems. Risk management is used to do a complete analysis to uncover the root cause of adverse events.

Cagliano et al. (2011) presented a systematic methodology to introduce the risks and their impacts on healthcare and patients in medical centers. They introduced the human reliability evaluation steps with elements of healthcare systems. Their methodology can minimize the risks and waste and enhance healthcare organizations and systems to obtain risk management. They applied their methodology to pharmacy systems.

Mendes and França (2024) analyzed the literature to discuss risk management in healthcare systems. Healthcare systems are faced with various issues like high costs and low-efficiency inpatient services. Healthcare management systems are the best solution to improve patient service quality, minimize risks, and minimize costs. They found that risk management can improve patient safety and services, employee safety, the importance of criteria to reduce risks, and combinations of tools and methods to improve healthcare systems.

Bunting Jr & Groszkruger (2016) introduced the transition into the focus on detecting errors and recommendations to improve healthcare systems. They introduced risk managers and other healthcare personnel to enhance healthcare systems.

La Pietra et al. (2005) provided an overview of the problems in healthcare systems. They discuss how to detect medical errors and clinical risk management to improve and increase patient safety. Their methodology uses better organizational performance to obtain better results. Various strategies, such as technology, communication, and information accessibility, can reduce risks and improve patient safety in healthcare systems.

Verbano and Venturini (2011) identified and characterized new directions for developing academic and managerial literature. Their methodology can aid risk management in identifying the most suitable directions. They applied their risk management to supply chain healthcare systems. Parker (2009) provided a framework to aid healthcare organizations in evaluating potential usefulness. Evaluating safety culture in risk management is essential to maximizing the interests of healthcare organizations. They applied his methodology in patient safety to evaluate the safety culture. His methodology covered various criteria of safety culture and five levels of safety.

Tukamuhabwa et al. (2023) provided a framework for exploring the link between supplier performance and other criteria, such as supply chain risk management abilities, logistic abilities, and internal social capital. They found that internal capital and supply chain risk management are significant for supplier performance. Ksibi et al. (2023) provided a complete review of the Internet of Medical Things (IoMT) and discussed the common risk evaluation approaches. Their proposed methodology improves trust and helps with risk exposure. It was built based on risk assessment and is applied in the risk assessment e-health context. Cybersecurity risk evaluation methods are deployed in various systems and organizations.

Ordunez et al. (2023) proposed a framework to minimize risk management in

healthcare. They provide their methodology for enhancing the accuracy of blood pressure measurement. Their methods provide a set of solutions to create a more effective health system.

Proposed Methodology

This section presents the steps of the neutrosophic approach integrated with two MCDM methods: CRITIC and ARAS. Single-Valued Neutrosophic Sets (SVNS) are employed to handle the uncertainty associated with the evaluation factors and alternatives. Figure 1 illustrates the proposed methodology. Additionally, this section provides key definitions related to SVNS. (Peng & Dai 2018):

Definition 1: The neutrosophic set has three elements such as truth $\(A_T(x)\)$, indeterminacy $A_I(x)$, and falsity $A_F(x)$. The sum of the three elements should be as

$$0 \leq \sup A_T(x) + \sup A_I(x) + \sup A_F(x) \leq 3 \quad (1)$$

Definition 2: SVN N can be presented as:

$$N = \{< x, T_N(x), I_N(x), F_N(x) > | x \in X\} \quad (2)$$

Definition 3: Let two SVNNs as $x = (T_x, I_x, F_x)\ and\ y = (T_y, I_y, F_y)$ Then their operations are presented as:

$$x^c = (F_x, 1 - I_x, T_x) \quad (3)$$

$$x \cup y = (\max\{T_x, T_y\}, \min\{I_x, I_y\}, \min\{F_x, F_y\}) \quad (4)$$

$$x \cap y = (\min\{T_x, T_y\}, \max\{I_x, I_y\}, \max\{F_x, F_y\}) \quad (5)$$

$$x \oplus y = (T_x + T_y - T_x * T_y, I_x * I_y, F_x * F_y) \quad (6)$$

$$x \otimes y = (T_x * T_y, I_x + I_y - I_x * I_y, F_x + F_y - F_x * F_y) \quad (7)$$

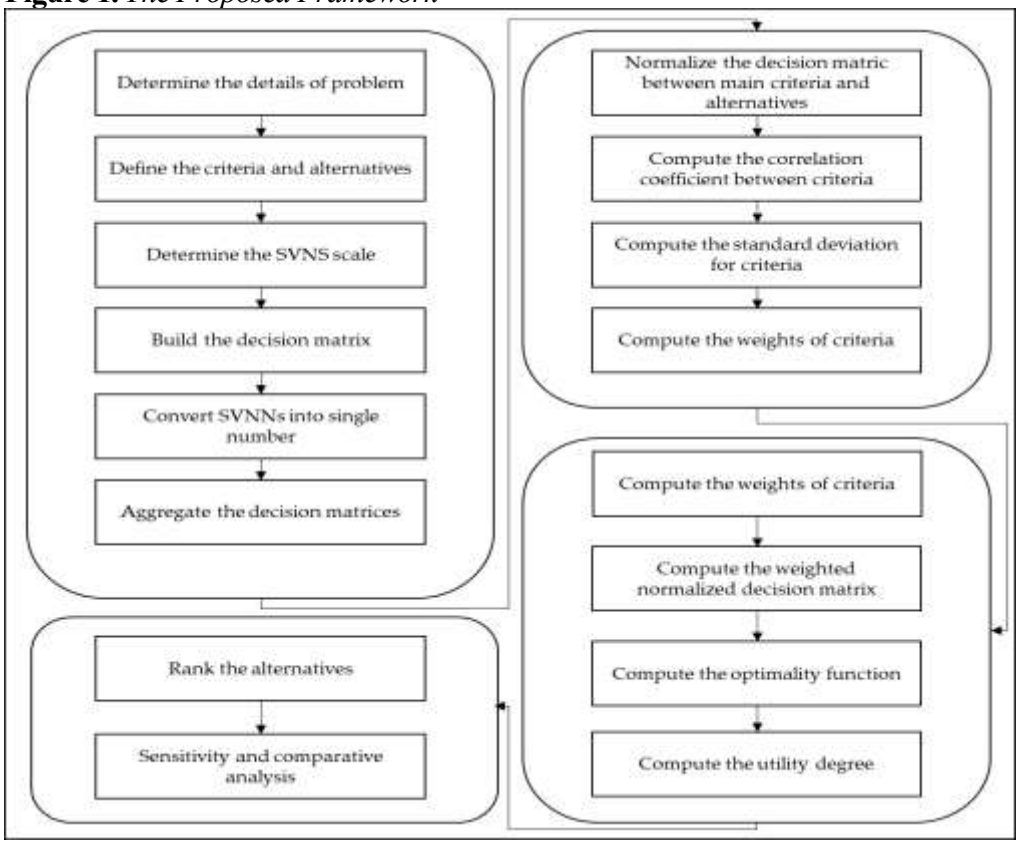
$$\lambda x = (1 - (1 - T_x)^\lambda, (I_x)^\lambda, 1 - (F_x)^\lambda), \lambda > 0 \quad (8)$$

$$x^\lambda = ((T_x^\lambda), (1 - I_x)^\lambda, (1 - F_x)^\lambda) \lambda > 0 \quad (9)$$

Definition 4: The score function of SVN can be computed as:

$$S(x) = \frac{2}{3} + \frac{T_x}{3} - \frac{I_x}{3} - \frac{F_x}{3} \quad (10)$$

Figure 1. *The Proposed Framework*



SVN-CRITIC-ARAS Method

This part introduces the steps of the SVN-CRITIC approach to obtain the weights of factors.

Step 1. Determine the details of the problem

This step studies the problem and computes all details of the problem. Define the main criteria to affect the selection of the best alternatives. Experts are invited to assess the factors and options. These experts have expertise in the risk management field and details of these experts are shown in Table 1. We define the criteria and alternatives and data is collected to assess the factors and options.

Step 2. Define the criteria and alternatives

The criteria and alternatives are determined based on previous studies and relevant literature. The opinions of experts are used to evaluate the factors and options. The factors of this work are defined as: $MMC_j = (MMC_1, MMC_2, \dots, MMC_n)\ with\ j = 1,2, \dots, n.$ The weights of the criteria are defined as $W_j = (w_1, w_1, \dots, w_n); w_j > 0; \sum_{j=1}^{n} w_j = 1$. The set of alternatives are defined as $MMA_i = (MMA_1, MMA_2, \dots, MMA_m)\ with\ i = 1,2, \dots, m.$

Step 3. Determine the SVNS scale

Define the set of SVNS linguistic terms and their single-valued neutrosophic numbers (SVNNs). These terms are used by experts to assess the factors, compute the factors' weights, and the best alternatives.

Step 4. Build the assessment matrix

The decision matrices are built between factors and options by a set of experts.

$$X = \begin{bmatrix} (T_{x_{11}}, I_{x_{11}}, F_{x_{11}}) & \cdots & (T_{x_{1n}}, I_{x_{1n}}, F_{x_{1n}}) \\ \vdots & \ddots & \vdots \\ (T_{x_{m1}}, I_{x_{m1}}, F_{x_{m1}}) & \cdots & (T_{x_{mn}}, I_{x_{mn}}, F_{x_{mn}}) \end{bmatrix}_{m \times n} \quad (11)$$

Step 5. Convert SVNNs into a single number

The score function is applied to obtain one number.

Step 6. Aggregate the decision matrices

The decision matrices between criteria and alternatives are aggregated into a single matrix.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}_{m \times n} \quad (12)$$

Step 7. Normalize the decision matrix between the main criteria and alternatives.

$$NX_{ij} = \frac{x_{ij} - x_{worst}}{x_{best} - x_{worst}}; i = 1,2,..,m; j = 1,2,\dots,n \quad (13)$$

Where $x_{worst} = \min x_i \ and \ x_{best} = \max x_i$.

Step 8. Compute the correlation coefficient between criteria

$$CC_{jk} = \frac{\sum_{i=1}^{m}(NX_{ij} - \overline{NX_j})(NX_{ik} - \overline{NX_k})}{\sqrt{\sum_{i=1}^{m}(NX_{ij} - \overline{NX_j})^2 \sum_{i=1}^{m}(NX_{ik} - \overline{NX_k})^2}} \quad (14)$$

Where $\overline{NX_j}$ can be computed as:

$$\overline{NX_j} = \frac{1}{n}\sum_{j}^{n} x_{ij}, i = 1,2,\dots,m \quad (15)$$

Step 9. Compute the standard deviation for criteria

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(NX_{ij} - \overline{NX_j}\right)^2}, i = 1,2,..,m; j = 1,2,\dots,n \quad (16)$$

And compute the amount of information for the criteria

$$R_j = \sigma_j \sum_{k=1}^{n}\left(1 - CC_{jk}\right), j = 1,2,\dots,n \quad (17)$$

Step 10. Compute the weights of the criteria

$$w_j = \frac{R_j}{\sum_{j=1}^{n} R_j} \quad (18)$$

Step 11. Compute the normalized decision matrix by ARAS method

$$U_{ij}^{*} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (19)$$

Step 12. Compute the weighted normalized decision matrix

$$L_{ij} = U_{ij}^{*} w_j \quad (20)$$

Step 13. Compute the optimality function

$$O_i = \sum_{j=1}^{n} L_{ij} \quad (21)$$

Step 14. Compute the utility degree

$$T_i = \frac{O_i}{E_0} \quad (22)$$

Where E_0 is the optimality value of O_i.

Step 15. Rank the projects.

The options are ordered based on the larger number of T_i.

Table 1. *Information of Experts in this Study*

	Experience	Field	Academic degree
Expert 1	30	Industry	PhD
Expert 2	15	Industry	M.SC
Expert 3	28	Industry	PhD
Expert 4	17	Academia	M.SC
Expert 5	25	Academia	PhD
Expert 6	20	Academia	M.SC

Results and Discussion

The main aim of this section is to apply the proposed methodology steps to obtain the weights of criteria and rank the alternatives. Figure 2 shows the criteria and alternatives of this study. This study used four alternatives:

Pro1: Device and Drug Management System

This project aims to digitalize medical products to enhance the effectiveness of the asset inventory and to minimize the number of duplicate data. This project has assets systems and materials systems.

Pro2: Health Operation Management System

This project aims to offer patients high-quality inpatient care. This project has a testing system, remote home care, and smart wards.

Pro3: Health Data Informational System

This project aims to combine information into computer hardware network communication and software. So, all information can be shared across all medical centers. This project has various benefits like cyber security, big data analysis, and artificial intelligence models.

Pro4: Health Administrative Information System

This project aims to combine various systems like administrative management, financial management, medical centers, medical administrative, and medical centers.

Step 1. The problem is determined, and all information is collected. The main aim of this study is to select the best SHMS with fewer risks. Six experts were identified as shown in Table 1.

Step 2. The set of criteria and alternatives are defined in this step as shown in Figure 2.

Step 3. Nine terms with their SVNNs are determined to evaluate the criteria and alternatives. These terms are used by experts and decision-makers to obtain the weights of criteria and rank the alternatives.

Step 4. The decision matrices between criteria and alternatives are built by Eq. (11) through six experts. These experts used the information in Table 1 to assess the factors and options. Table 2 shows the decision matrices between criteria and alternatives and Table 3 shows other opinions of experts.

Step 5. The SVNNs are converted by using the score function to obtain a single value.

Step 6. Combined the decision matrices into a single matrix.

Step 7. The normalized assessment matrix is obtained by Eq. (13) as presented in Table 4. There are only three criteria that are worst operation cost, investment cost, and maintenance cost and other criteria are best.

Step 8. The correlation coefficient between criteria is obtained by Eq. (14).

Step 9. The standard deviation of every criterion is computed by Eq. (16). The amount of information for the main criteria is obtained by Eq. (17).

Step 10. The weights of the criteria are obtained by Eq. (18) as shown in Figure 3.

Step 11. We applied the steps of the SVN-ARAS method to rank the alternatives. The normalized decision matrix is obtained by Eq. (19) as presented in Table 5.

Step 12. The weighted normalized assessment matrix is obtained by Eq. (20) as presented in Table 6.

Step 13. The optimality function is obtained by Eq. (21).

Step 14. The utility degree is obtained using Eq. (22).

Step 15. The rank of the alternatives is shown in Figure 4.

Figure 2. *The Criteria and Alternatives of this Study*

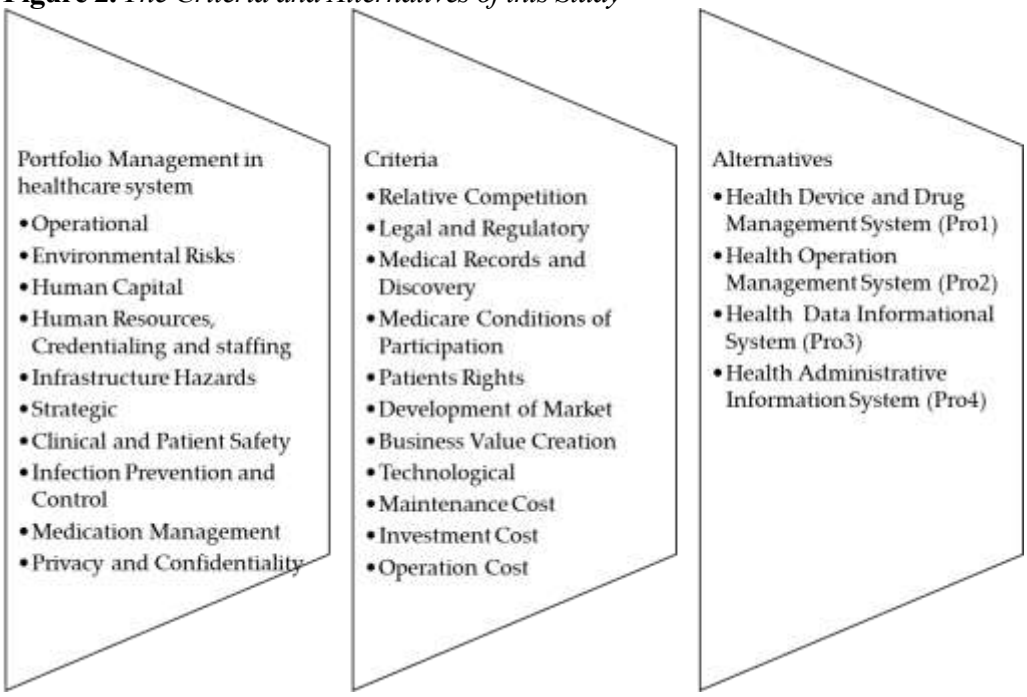


Figure 3. *The Weights of the Main Criteria*

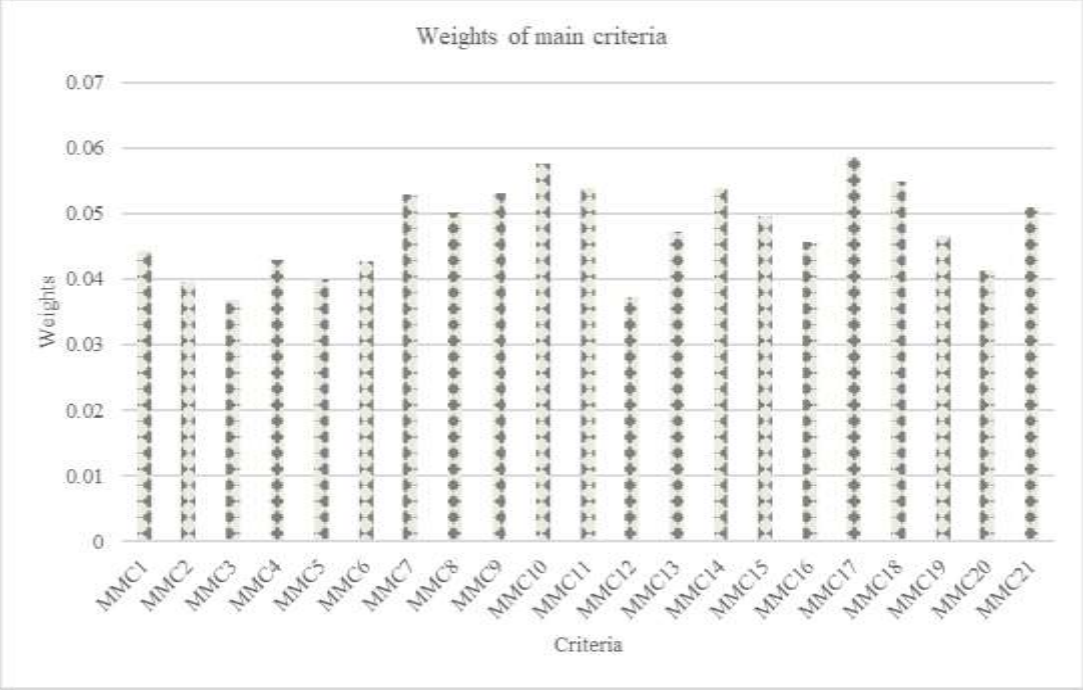


Figure 4. *The Utility Degree Values*

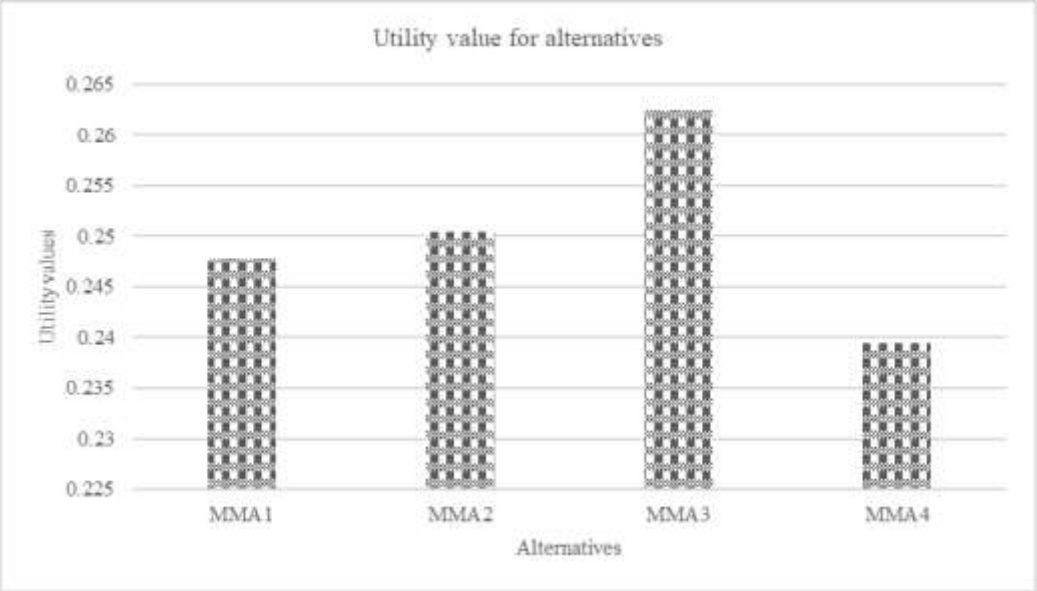


Table 2. *Decision Matrices by Opinions of First Experts*

	MMA_1	MMA_2	MMA_3	MMA_4
MMC_1	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.1,0.9,0.9)
MMC_2	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.2,0.8,0.9)
MMC_3	(0.8,0.2,0.3)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.3,0.7,0.8)
MMC_4	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.5,0.5,0.5)
MMC_5	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.4,0.6,0.7)
MMC_6	(0.5,0.5,0.5)	(0.3,0.7,0.8)	(0.4,0.6,0.7)	(0.3,0.7,0.8)
MMC_7	(0.5,0.5,0.5)	(0.3,0.7,0.8)	(0.4,0.6,0.7)	(0.2,0.8,0.9)
MMC_8	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.3,0.7,0.8)	(0.1,0.9,0.9)
MMC_9	(0.3,0.7,0.8)	(0.4,0.6,0.7)	(0.2,0.8,0.9)	(0.9,0.1,0.2)
MMC_{10}	(0.2,0.8,0.9)	(0.8,0.2,0.3)	(0.1,0.9,0.9)	(0.8,0.2,0.3)
MMC_{11}	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.6,0.4,0.5)
MMC_{12}	(0.9,0.1,0.2)	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.5,0.5,0.5)
MMC_{13}	(0.8,0.2,0.3)	(0.3,0.7,0.8)	(0.8,0.2,0.3)	(0.4,0.6,0.7)
MMC_{14}	(0.7,0.3,0.4)	(0.4,0.6,0.7)	(0.8,0.2,0.3)	(0.9,0.1,0.2)
MMC_{15}	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
MMC_{16}	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.7,0.3,0.4)
MMC_{17}	(0.4,0.6,0.7)	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.7,0.3,0.4)
MMC_{18}	(0.3,0.7,0.8)	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.6,0.4,0.5)
MMC_{19}	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
MMC_{20}	(0.2,0.8,0.9)	(0.3,0.7,0.8)	(0.3,0.7,0.8)	(0.4,0.6,0.7)
MMC_{21}	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)

Table 3. *Decision Matrices by Opinions of Experts*

Second Expert	MMA_1	MMA_2	MMA_3	MMA_4
MMC_1	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
MMC_2	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.8,0.2,0.3)
MMC_3	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.6,0.4,0.5)
MMC_4	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.8,0.2,0.3)	(0.4,0.6,0.7)
MMC_5	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.2,0.8,0.9)
MMC_6	(0.2,0.8,0.9)	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.1,0.9,0.9)
MMC_7	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.2,0.8,0.9)	(0.9,0.1,0.2)
MMC_8	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.1,0.9,0.9)	(0.7,0.3,0.4)
MMC_9	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.6,0.4,0.5)
MMC_{10}	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.9,0.1,0.2)
MMC_{11}	(0.1,0.9,0.9)	(0.8,0.2,0.3)	(0.9,0.1,0.2)	(0.8,0.2,0.3)
MMC_{12}	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.6,0.4,0.5)
MMC_{13}	(0.9,0.1,0.2)	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.9,0.1,0.2)
MMC_{14}	(0.8,0.2,0.3)	(0.2,0.8,0.9)	(0.4,0.6,0.7)	(0.8,0.2,0.3)
MMC_{15}	(0.6,0.4,0.5)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.6,0.4,0.5)
MMC_{16}	(0.4,0.6,0.7)	(0.9,0.1,0.2)	(0.1,0.9,0.9)	(0.4,0.6,0.7)
MMC_{17}	(0.2,0.8,0.9)	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.2,0.8,0.9)
MMC_{18}	(0.1,0.9,0.9)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.1,0.9,0.9)
MMC_{19}	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.9,0.1,0.2)
MMC_{20}	(0.7,0.3,0.4)	(0.3,0.7,0.8)	(0.6,0.4,0.5)	(0.7,0.3,0.4)
MMC_{21}	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
Third Expert				
MMC_1	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.1,0.9,0.9)
MMC_2	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.2,0.8,0.9)
MMC_3	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.4,0.6,0.7)	(0.2,0.8,0.9)
MMC_4	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.1,0.9,0.9)
MMC_5	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.7)
MMC_6	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.5,0.5,0.5)	(0.6,0.4,0.5)
MMC_7	(0.4,0.6,0.7)	(0.5,0.5,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
MMC_8	(0.7,0.3,0.4)	(0.4,0.6,0.7)	(0.7,0.3,0.4)	(0.5,0.5,0.5)
MMC_9	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.4,0.6,0.7)
MMC_{10}	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.7,0.3,0.4)
MMC_{11}	(0.1,0.9,0.9)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
MMC_{12}	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.2,0.8,0.9)
MMC_{13}	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.8,0.2,0.3)	(0.1,0.9,0.9)
MMC_{14}	(0.1,0.9,0.9)	(0.7,0.3,0.4)	(0.8,0.2,0.3)	(0.4,0.6,0.7)
MMC_{15}	(0.4,0.6,0.7)	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.6,0.4,0.5)
MMC_{16}	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.6,0.4,0.5)
MMC_{17}	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
MMC_{18}	(0.5,0.5,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.4,0.6,0.7)
MMC_{19}	(0.4,0.6,0.7)	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.7,0.3,0.4)
MMC_{20}	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.3,0.7,0.8)	(0.9,0.1,0.2)
MMC_{21}	(0.9,0.1,0.2)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
Fourth Expert				
MMC_1	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.1,0.9,0.9)
MMC_2	(0.8,0.2,0.3)	(0.6,0.4,0.5)	(0.8,0.2,0.3)	(0.2,0.8,0.9)
MMC_3	(0.2,0.8,0.9)	(0.2,0.8,0.9)	(0.7,0.3,0.4)	(0.2,0.8,0.9)

MMC_4	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.6,0.4,0.5)	(0.1,0.9,0.9)
MMC_5	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.5,0.5,0.5)	(0.4,0.6,0.7)
MMC_6	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
MMC_7	(0.2,0.8,0.9)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
MMC_8	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.3,0.7,0.8)	(0.5,0.5,0.5)
MMC_9	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.4,0.6,0.7)
MMC_{10}	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.2,0.8,0.9)	(0.2,0.8,0.9)
MMC_{11}	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.1,0.9,0.9)	(0.1,0.9,0.9)
MMC_{12}	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.4,0.6,0.7)
MMC_{13}	(0.4,0.6,0.7)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)
MMC_{14}	(0.7,0.3,0.4)	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.6,0.4,0.5)
MMC_{15}	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
MMC_{16}	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.4,0.6,0.7)	(0.4,0.6,0.7)
MMC_{17}	(0.4,0.6,0.7)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.7,0.3,0.4)
MMC_{18}	(0.7,0.3,0.4)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
MMC_{19}	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
MMC_{20}	(0.2,0.8,0.9)	(0.3,0.7,0.8)	(0.3,0.7,0.8)	(0.4,0.6,0.7)
MMC_{21}	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
Fifth Expert				
MMC_1	(0.9,0.1,0.2)	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.2,0.8,0.9)
MMC_2	(0.8,0.2,0.3)	(0.1,0.9,0.9)	(0.8,0.2,0.3)	(0.1,0.9,0.9)
MMC_3	(0.8,0.2,0.3)	(0.4,0.6,0.7)	(0.2,0.8,0.9)	(0.2,0.8,0.9)
MMC_4	(0.7,0.3,0.4)	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.2,0.8,0.9)
MMC_5	(0.6,0.4,0.5)	(0.1,0.9,0.9)	(0.4,0.6,0.7)	(0.1,0.9,0.9)
MMC_6	(0.5,0.5,0.5)	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.4,0.6,0.7)
MMC_7	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.2,0.8,0.9)
MMC_8	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.2,0.8,0.9)	(0.1,0.9,0.9)
MMC_9	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.1,0.9,0.9)	(0.4,0.6,0.7)
MMC_{10}	(0.1,0.9,0.9)	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
MMC_{11}	(0.4,0.6,0.7)	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.2,0.8,0.9)
MMC_{12}	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.1,0.9,0.9)
MMC_{13}	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.4,0.6,0.7)
MMC_{14}	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.4,0.6,0.7)	(0.6,0.4,0.5)
MMC_{15}	(0.4,0.6,0.7)	(0.6,0.4,0.5)	(0.7,0.3,0.4)	(0.6,0.4,0.5)
MMC_{16}	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.9,0.1,0.2)	(0.5,0.5,0.5)
MMC_{17}	(0.9,0.1,0.2)	(0.5,0.5,0.5)	(0.9,0.1,0.2)	(0.4,0.6,0.7)
MMC_{18}	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.7,0.3,0.4)
MMC_{19}	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.7,0.3,0.4)	(0.9,0.1,0.2)
MMC_{20}	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.9,0.1,0.2)	(0.4,0.6,0.7)
MMC_{21}	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)
Sixth Expert				
MMC_1	(0.9,0.1,0.2)	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.2,0.8,0.9)
MMC_2	(0.8,0.2,0.3)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.1,0.9,0.9)
MMC_3	(0.8,0.2,0.3)	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.2,0.8,0.9)
MMC_4	(0.2,0.8,0.9)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.1,0.9,0.9)
MMC_5	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.6,0.4,0.5)	(0.4,0.6,0.7)
MMC_6	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.6,0.4,0.5)
MMC_7	(0.6,0.4,0.5)	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.6,0.4,0.5)

MMC_8	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.5,0.5,0.5)
MMC_9	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.4,0.6,0.7)
MMC_{10}	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.4,0.6,0.7)	(0.2,0.8,0.9)
MMC_{11}	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.2,0.8,0.9)	(0.1,0.9,0.9)
MMC_{12}	(0.6,0.4,0.5)	(0.2,0.8,0.9)	(0.1,0.9,0.9)	(0.4,0.6,0.7)
MMC_{13}	(0.5,0.5,0.5)	(0.1,0.9,0.9)	(0.2,0.8,0.9)	(0.6,0.4,0.5)
MMC_{14}	(0.4,0.6,0.7)	(0.4,0.6,0.7)	(0.1,0.9,0.9)	(0.6,0.4,0.5)
MMC_{15}	(0.7,0.3,0.4)	(0.6,0.4,0.5)	(0.4,0.6,0.7)	(0.5,0.5,0.5)
MMC_{16}	(0.9,0.1,0.2)	(0.6,0.4,0.5)	(0.6,0.4,0.5)	(0.4,0.6,0.7)
MMC_{17}	(0.7,0.3,0.4)	(0.5,0.5,0.5)	(0.6,0.4,0.5)	(0.7,0.3,0.4)
MMC_{18}	(0.9,0.1,0.2)	(0.4,0.6,0.7)	(0.5,0.5,0.5)	(0.9,0.1,0.2)
MMC_{19}	(0.2,0.8,0.9)	(0.7,0.3,0.4)	(0.4,0.6,0.7)	(0.5,0.5,0.5)
MMC_{20}	(0.2,0.8,0.9)	(0.9,0.1,0.2)	(0.7,0.3,0.4)	(0.4,0.6,0.7)
MMC_{21}	(0.1,0.9,0.9)	(0.1,0.9,0.9)	(0.9,0.1,0.2)	(0.9,0.1,0.2)

Table 4. *Normalized Decision Matrix by Critic Methods*

	MMA_1	MMA_2	MMA_3	MMA_4
MMC_1	1	0.4	1	0
MMC_2	1	0.311688	0.727273	0
MMC_3	1	0.492063	0.634921	0
MMC_4	0.875	0.875	1	0
MMC_5	0.6	0.675	1	0
MMC_6	1	0	0.272727	0.545455
MMC_7	0.275862	0.310345	0	1
MMC_8	1	0.888889	0	0.814815
MMC_9	0.263158	0.473684	0	1
MMC_{10}	0	1	0.5	0.904762
MMC_{11}	0	0.930233	1	0.534884
MMC_{12}	1	0.523077	0.676923	0
MMC_{13}	0.823529	0	1	0.117647
MMC_{14}	0.296296	0	0.148148	1
MMC_{15}	0.6875	0.4375	0	1
MMC_{16}	0.5	1	0.157895	0
MMC_{17}	0	0.896552	1	0.034483
MMC_{18}	0	0.695652	1	0.869565
MMC_{19}	1	0	1	0.466667
MMC_{20}	1	0	0.714286	0.571429
MMC_{21}	0.8	1	0.052174	0

Table 5. *Normalized Decision Matrix by Aras Methods*

	MMA_1	MMA_2	MMA_3	MMA_4
MMC_1	0.340909	0.204545	0.340909	0.113636
MMC_2	0.363363	0.204204	0.3003	0.132132
MMC_3	0.343949	0.242038	0.270701	0.143312
MMC_4	0.280822	0.280822	0.30137	0.136986
MMC_5	0.254181	0.264214	0.307692	0.173913
MMC_6	0.270833	0.232639	0.243056	0.253472
MMC_7	0.23741	0.241007	0.208633	0.31295

MMC_8	0.282528	0.271375	0.182156	0.263941
MMC_9	0.239344	0.252459	0.222951	0.285246
MMC_{10}	0.174174	0.3003	0.237237	0.288288
MMC_{11}	0.167702	0.291925	0.301242	0.23913
MMC_{12}	0.324808	0.245524	0.2711	0.158568
MMC_{13}	0.265753	0.227397	0.273973	0.232877
MMC_{14}	0.245333	0.224	0.234667	0.296
MMC_{15}	0.256281	0.246231	0.228643	0.268844
MMC_{16}	0.258065	0.305211	0.225806	0.210918
MMC_{17}	0.216346	0.278846	0.286058	0.21875
MMC_{18}	0.212276	0.253197	0.2711	0.263427
MMC_{19}	0.210884	0.312925	0.210884	0.265306
MMC_{20}	0.225	0.283333	0.241667	0.25
MMC_{21}	0.146667	0.085333	0.376	0.392

Table 6. *The Weighted Normalized Decision Matrix*

	MMA_1	MMA_2	MMA_3	MMA_4
MMC_1	0.015111	0.009067	0.015111	0.005037
MMC_2	0.014362	0.008071	0.01187	0.005223
MMC_3	0.012694	0.008933	0.009991	0.005289
MMC_4	0.012075	0.012075	0.012958	0.00589
MMC_5	0.010144	0.010544	0.012279	0.006941
MMC_6	0.011557	0.009927	0.010372	0.010816
MMC_7	0.01257	0.01276	0.011046	0.016569
MMC_8	0.014161	0.013602	0.00913	0.013229
MMC_9	0.012716	0.013413	0.011845	0.015154
MMC_{10}	0.010045	0.017319	0.013682	0.016626
MMC_{11}	0.009044	0.015743	0.016245	0.012896
MMC_{12}	0.012084	0.009135	0.010086	0.005899
MMC_{13}	0.012529	0.01072	0.012916	0.010979
MMC_{14}	0.013221	0.012071	0.012646	0.015951
MMC_{15}	0.012709	0.012211	0.011338	0.013332
MMC_{16}	0.011776	0.013927	0.010304	0.009624
MMC_{17}	0.012665	0.016323	0.016745	0.012805
MMC_{18}	0.011634	0.013877	0.014858	0.014438
MMC_{19}	0.009839	0.0146	0.009839	0.012378
MMC_{20}	0.009311	0.011725	0.010001	0.010346
MMC_{21}	0.007484	0.004354	0.019186	0.020002

Analysis

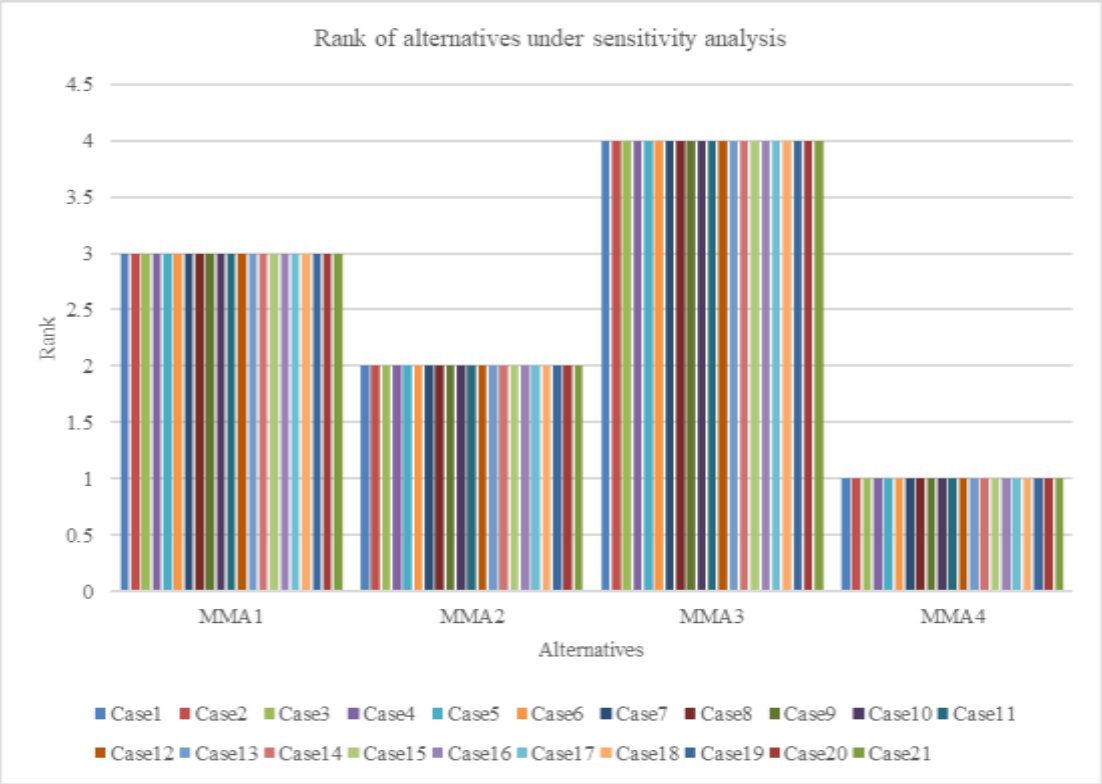
This part introduces the results of sensitivity and comparative analysis.

Sensitivity Analysis

This part introduces the sensitivity analysis to display the stability of order. We proposed 21 cases to alter the weights of factors. We put the first criterion with 0.05

weight and others are equal. In the second case, we put the second criterion with 0.05 and other factors are equal. Then we rank the projects under different cases as shown in Figure 5. We demonstrate the order of projects is stable through various cases.

Figure 5. *The Order of Projects through Sensitivity Analysis*



Comparative Analysis

This part compares the rank of the proposed method with other MCDM methods as shown in Table 7. We compare the proposed method with other MCDM methods like TOPSIS, VIKOR, MABAC, and COPRAS. These methods are compared under SVNS. We used the weights of criteria in the CRITIC method in all methods. We show the effectiveness of the proposed approach with other MCDM approaches.

Table 7. *Results Comparative Analysis*

	Proposed method	SVN-TOPSIS	SVN-VIKOR	SVN-MABAC	SVN-COPRAS
MMA_1	2	3	1	2	2
MMA_2	3	2	3	3	3
MMA_3	4	4	4	4	4
MMA_4	1	1	2	1	1

Conclusions

This study proposed an MCDM methodology for selecting the best project for SHMS to reduce risk in healthcare systems. Risk management is the best process for identifying and mitigating risks in SHMS. So, we recognize the risks of SHMS and select the best project with fewer risks. We applied the MCDM framework to deal with conflict factors. We used the CRITIC and ARAS methods. The CRITIC approach is applied to obtain the factors' weights, and the ARAS approach is used to order the projects. The MCDM methods are integrated with SVNSs to deal with uncertain information. We invited six experts to evaluate the criteria and options using linguistic terms. Then, we used their SVNNs to assess the requirements and projects. The decision matrix is used to compute the criteria weights using CRITIC methods. We collected 21 criteria and 4 alternatives. The ARAS method used the decision matrix and normalization decision matrix to rank the other options. The results show that the Health Data Informational System is the best project with fewer risks. The sensitivity analysis presents the order of alternatives as stable through multiple cases. The comparative study shows that the proposed method is more effective than the MCDM methods.

The various NS extensions can be applied in this study in rework, like Type-2 neutrosophic sets. There are various MCDM methods can be applied to show the weights of factors and rank the alternatives like AHP, TOPSIS, and VIKOR

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Undergraduate Social Care and Healthcare Applicants' Emotional Intelligence and Factors Related to it: A Cross-sectional Study

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Aim: To assess undergraduate social and healthcare applicants' emotional intelligence and the factors related to it. Background: Emotional intelligence enhances study success. It also reduces stress enabling the management of emotional stressors in social and healthcare environments. However, applicants' emotional intelligence and the factors related to it have been scarcely researched. Methods: The Emotional Intelligence Test (EMI-T) was used in 4, 808 social and healthcare applicants during the national digital entrance examination in 2021. The data were analysed with descriptive statistics, an analysis of variance with Tukey's test in post-hoc multiple-group comparisons and a regression analysis. Results: The applicants scored best at managing emotions and their emotional intelligence mean score was above the centre of the score range. Female gender, older age, previous education, having currently employed parents and the applicant or his/her parents being born in Finland indicated higher emotional intelligence. However, these factors explained only 14% of emotional intelligence variation. Conclusions: Social and healthcare applicants managed overall well in EMI-T. Several demographic factors seem to influence applicants' emotional intelligence to a minor degree. Further research should establish how the domains of daily life (resolution of past life events, relationships, and self-esteem) and demographic factors together explain emotional intelligence.

Keywords: *emotional intelligence; student selection; social care education; healthcare education; assessment*

Introduction

Emotional intelligence (EI) can be defined as a range of abilities, including the verbal and non-verbal appraisal, expression, management and acceptance of emotions in oneself and others. EI also consists of the ability to use emotions to achieve goals and solve problems (Mayer et al. 2016, Pienimaa et al. 2021). EI can

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be divided to trait EI, ability EI and mixed EI where EI is considered both trait and ability. Trait EI is typically measured using self-report measures and ability EI is usually measured using objective ability-type measures (Goleman 1995, Bar-On 2006, Petrides et al. 2007, Mayer et al. 2016.) EI is needed in social and healthcare education to cope with emotionally challenging clinical environments (Litvack et al. 2010, Michelangelo 2015, Lewis et al. 2017, Pienimaa et al. 2022a). Educational institutions aim to select students who have the necessary abilities to complete their studies. Student selection should be objective and fair for the applicants (Rankin 2013), thus in this study objective ability EI assessment is used.

There are indications that social care and healthcare students may have higher-than-average EI scores (Joseph et al. 2015, Stanley and Mettilda 2021). Štiglic et al. (2018) and Snowden et al. (2015) also discovered that healthcare students scored significantly higher regarding EI than engineering or computing students. However, Talman et al. (2020) reported that nursing applicants differ in terms of EI, and some studies have indicated that healthcare students can have low EI scores (Cerit and Beser 2014). Those with low EI may be at risk of emotional distress, which can affect their study success (Lewis et al. 2017).

Previous social care and healthcare studies have researched mainly nursing and medical students', demographic factors relationship to EI (Cerit and Besser 2004, Van Rooy et al. 2005, Joseph et al. 2015, Stanley and Metilda 2018). However, to our knowledge, only two studies (Carrothers et al. 2000, Talman et al. 2020) have assessed the relationship between EI and demographic factors in the student selection context. According to these studies, female gender (Carrothers et al. 2000, Talman et al. 2020), older age and previous education (Talman et al. 2020) were related to higher EI scores among healthcare applicants.

Older age and female gender have also been identified as factors affecting social care and healthcare students' EI positively (Arora et al. 2010, Joseph et al. 2015, Snowden et al. 2015; Aithal et al. 2016; Stanley and Metilda 2018; Asimopoulos et al. 2020). However, some study results indicate that age and gender have no significant relationship to EI among healthcare students (Cerit and Beser 2014, Joseph et al. 2015, Štiglic et al. 2018). There are also a few studies reporting that males have higher EI scores than females (Carr 2009, Khraisat et al. 2015).

The previous research studying EI's relationship to socio-economic status (SES) or ethnicity in social care and healthcare students is scarce. Joseph et al. (2015) found that SES was not correlated with EI. There are indications that healthcare students of a white ethnic origin score higher than minority ethnic groups regarding EI (Todres et al. 2010), but there are other studies indicating the opposite (Van Rooy et al. 2005, Carr 2009). There are still other studies indicating no relationship between ethnic groups and EI (Joseph et al. 2015, Khraisat et al. 2015). However, there are indications that EI may be culturally sensitive (Zhang and Cross 2011, Johnsen et al. 2012), even though there is evidence that at least some categories of EI are intercultural phenomena (Scherer et al. 2011).

To conclude, according to a review on literature, the previous literature comparing various demographic factors and EI have had controversial results in all factors that have previously been studied, and only few studies have previously assessed the factors specifically related to EI in the student-selection context

(Carrothers et al. 2000, Talman et al. 2020). So, there is no conclusive information about the factors affecting social care and healthcare applicants EI. Thus, more research is needed to investigate which demographic factors are related to EI in student selection. This information is important because EI has an impact on study success (Pienimaa et al. 2022a) and it is crucial to identify those applicants who may need more support to finish their studies successfully.

Student selection is a high-stake situation where selection methods should be objective and fair to applicants. In other words, demographic factors should not affect the assessment (Rankin 2013). Thus, it is important to assess if the use of EMI-T in student selection is valid. The content validity and psychometric evaluation of the EMI-T have been reported in a previous study (Pienimaa et al. 2022a). Therefore, this study focuses on assessing test fairness and whether background variables are related to the applicants' test scores. This is important for identifying construct-irrelevant characteristics that may threaten the validity of the test. A fair test should measure the intended construct and minimize the risk for test being affected by construct-irrelevant characteristics such as linguistic or cultural characteristics (American Educational Research Association, American Psychological Association and National Council on Measurement in Education 2014).

The context of this study is set in the student selection of Finnish Universities of Applied Sciences. Bachelor's degree in social care and healthcare is provided in 20 Universities of Applied Sciences nationwide in Finland. The length of degrees varies from 210 to 270 ECTS credits. The expected time of graduation is from 3,5 years to 4,5 years depending on the programme (e.g. nursing, social services, physiotherapy, midwifery and paramedics) (Ministry of Education and Culture 2021).

Materials and Methods

Aim

The aim of the study was to assess undergraduate social care and healthcare applicants' emotional intelligence and the factors related to it and assess whether fair student selection is possible with EMI-T.

The research questions were: What is the EI level of undergraduate social care and healthcare applicants? What factors explain undergraduate social care and healthcare applicants' EI? Is EMI-T a fair assessment method to assess EI of undergraduate social care and healthcare applicants?

The Emotional Intelligence Test (EMI-T) was developed to assess both social care and healthcare applicants' EI because social and healthcare professionals often work together in multi-disciplinary teams to provide comprehensive care to patients and clients. Also, social care and healthcare education share common core components (Eriksson et al. 2015, GANES 2019, Stanley and Mettilda 2021, Pienimaa et al. 2022a.) Furthermore, EI does not seem to be different between social care and healthcare students (Snowden et al. 2015).

Design

A cross-sectional design was used to obtain data from social care and healthcare applicants during their entrance examination.

Sample and Participants

In total, 21,916 undergraduate (bachelor's level) applicants to social, health and rehabilitation study programmes in 20 Finnish Universities of Applied Sciences (UASs) participated in the UAS Exam on eight selection days during spring 2021. EMI-T was an official part of the UAS Exam, which all participants were required to complete. The participants in this study were all 4,808 applicants, who completed the EMI-T as part of the UAS Exam on two selection days, 31 May or 4 June 2021 (a version of the EMI-T that was used in this study was conducted to the applicants during those days) and gave their consent to participate in the research. Thus, purposive sampling method including entire population that took the test and gave consent was used (total population sampling). The information about the study was contained in the invitation letter that the applicants had access several weeks before the entrance examination.

Data Collection

The data were collected through the validated test EMI-T, which includes 20 multiple-choice items within four EI subscales (perception and understanding of emotions [eight items, maximum subscale score 8], acceptance of emotions [four items, maximum subscale score 4], management of emotions [four items, maximum subscale score 4] and social awareness and relations [four items, maximum subscale score 4]; Pienimaa et al. 2022b). Each item includes one correct response option and three incorrect ones. Each correct response yields 1 point, and unanswered or incorrect responses yield 0 points. Maximum score for the test is 20 points. The EMI-T consists of case-based questions and questions related to facial recognition. The time limit for the EMI-T is 20 minutes.

The content of the EMI-T (i.e., the relevance and clarity of the items) was evaluated by three expert panels, and a psychometric assessment of the test was based on Item Response Theory (IRT) analysis (Pienimaa et al. 2022b). IRT was used because it can provide detailed item level evaluation including the evaluation of distractors (i.e., incorrect response options). From the student selection perspective, the selection test should be able to arrange applicants in rank order based on their performance. IRT can evaluate the difficulty level of the items and the test´s ability to differentiate applicants' skills in the different ability levels (Tavakol et al. 2014, Gierl et al. 2017). The quality of distractors is also essential because it affects the difficulty level of the items (DeVellis 2017, Gierl et al. 2017, Li et al. 2019).

According to the results of IRT, most of the items were easy, however they were ambiguous, and EMI-T can differentiate applicants' abilities in the upper ability level, thus only approximately 5% of applicants achieved maximum scores.

There was also a positive and statistically significant correlation between subscales and between subscales and the total score, supporting the structural validity of the test.

The demographic factors (i.e., age, gender, previous education, place of birth, parents' place of birth, parents' employment status and participation in a preparation course specifically tailored to the entrance examination) were available and collected from the entrance examination system. The background information collected was based on previous studies and the student-selection development process (Talman et al. 2018, Vierula et al. 2021a).

The EMI-T was used as a part of the national joint UAS Exam. The purpose of the joint UAS Exam is to measure the abilities needed to succeed in the UAS studies. It measures social care and healthcare applicants' abilities in reasoning, language and communication, mathematics, ethics and EI. Selection is based on overall performance, and not on any individual section score. However, applicants must achieve a minimum score on each section to be considered for the selection process. Total scores are used to rank applicants in terms of their performance on the UAS Exam and thus inform the selection decision. The UAS Exam is on-site digital test with multiple choice questions, and the test is taken under supervision (Vierula et al. 2021a).

Ethical Considerations

The study followed the ethical principles specified by the National Advisory Board on Research Ethics (The Finnish Advisory Board on Research Integrity 2012). Approvals were obtained from the participating UASs and the Human Sciences Ethics Committee in the Satakunta region on 14 May 2021, before beginning the study. The participants were informed regarding their continued anonymity, their ability to withdraw from the study and the voluntary nature of the study. Withdrawal from the study was possible at any point via contacting the researchers, and the departing participant's research data were not used in the research after this point. However, the participants were also informed that any data analysis performed prior to their withdrawal could not be reversed. This information was contained in the invitation letter, data protection statement and informed consent form. The participants gave their informed consent prior to the beginning of the UAS Exam by choosing a relevant response regarding participation (yes/no).

Data Analysis

Descriptive statistics (frequencies and percentages) and Pearson correlation coefficient were used to assess the EI level of undergraduate social care and healthcare applicants. Descriptive statistics (frequencies and percentages) were calculated to describe the participants' demographic factors and summarise their EMI-T scores. Pearson correlation coefficient was used to assess the dependencies between the sub-scores and the total score.

Analysis of variance (ANOVA) with Tukey's test in post-hoc multiple-group comparisons and multiple linear regression were used to determine what factors explain undergraduate social care and healthcare applicants' EI. Multiple linear

regression was also used to determine whether the EMI-T is a fair assessment method to assess EI of undergraduate social care and healthcare applicants. Analysis of variance (ANOVA) with Tukey's test in post-hoc multiple-group comparisons was used to assess the factors related to applicants' EI. ANOVA was first used to determine the statistical significance of the various factors related to EI variation. Tukey's test was performed to further analyse the different factors relation to EI (Table 4). Multiple linear regression was used to determine the degree to which various factors explain the variation in applicants' EI. In most of the previous studies multiple regression analysis has not been used to assess how the different factors explain together the level of EI. For this study, it was important to evaluate whether EMI-T is a fair assessment method to assess EI of undergraduate social care and healthcare applicants. All demographic factors were entered simultaneously to the model. Parents' working status was not included in the regression analysis, due to small sample sizes in some subgroups. The threshold of statistical significance was set at 0.05 (Wasserstein and Lazar 2016). The data were analysed with the Python programming language, using Statsmodels libraries (https://www.statsmodels.org/stable/index.html). EI was assessed using mean EMI-T scores, observing whether a given score was above or below the centre of the range of possible scores. Mean scores close to the centre of the range are desirable in that, generally, the items that have mean values near to an extreme of the response range have low variance and do not correlate with other items (DeVellis 2017, Vierula et al. 2021b).

Results

Participants' Demographic Characteristics

The participants were mostly female (80.3%) and had a high school (44.4%) or vocational school (39.9%) education prior to their application. About half of the participants were under 25 years old (51.7%). Most of the applicants (93.3%) and their parents (75.1%) were born in Finland, and most of the parents were employed (85.0%; Table 1.)

Table 1. *Demographic Information regarding the Participants*

Demographic information	n	%
Age (years) (n = 4,808, missing 0)		
Under 20	712	14.8
20–24	1772	36.9
25–29	824	17.1
Over 29	1500	31.2
Gender (n = 4,808, missing 0)		
Female	3862	80.3
Male	946	19.7
Previous education (n = 4,808, missing 0)		
High school	2134	44.4
Vocational school	1920	39.9
Higher education	440	9.2
Other	314	6.5

Place of birth (n = 4,808, missing 0)		
Finland	4484	93,3
Other country	324	6.7
Parents' place of birth (n = 4,808, missing 0)		
Finland	3610	75.1
Other country	1198	24.9
Father's employment status (n = 4,509, missing n = 299)		
Self-employed persons	857	19.0
Upper-level employees	628	13.9
Lower-level employees	790	17.5
Manual workers	1561	34.6
Students	28	0.6
Pensioners	485	10.8
Unemployed	160	3.5
Mother's employment status (n = 4,641, missing n = 167)		
Self-employed persons	404	8.7
Upper-level employees	472	10.2
Lower-level employees	1167	25.1
Manual workers	1901	41.0
Students	64	1.4
Pensioners	416	9.0
Unemployed	217	4.7
Participation in the training course (n = 4,808, missing 0)		
Yes	551	11.5
No	4257	88.5

Social Care and Healthcare Applicants' Emotional Intelligence

The total mean EI score of the social care and healthcare applicants (n=4 808) was above the centre of the score range (half of the applicants scored at least 16 points), indicating that they performed well in the EI section of the UAS Exam. The applicants performed well on all EI subscales, but they seemed to perform best in the management of emotions and at least half of the applicants achieved the highest possible score on this subscale. The applicants seemed to perform least well in the perception and understanding of emotions subscale and less than 5% of the applicants achieved the highest possible score on this subscale (Table 2).

Table 2. *EI Scores of Social Care and Healthcare Applicants*

EI scores	Mean/Maximum score	Centre of the score range	SD	Min	Max	50%[1]	75%[2]
total score	15.92/20	10	2,16	0	20	16.00	17.00
perception and understanding of emotions	5.34/8	4	1.23	0	8	5.00	6.00
acceptance of emotions	3.41/4	2	0.80	0	4	4.00	4.00
management of emotions	3.63/4	2	0.65	0	4	4.00	4.00
social awareness and relations	3.54/4	2	0.69	0	4	4.00	4.00

[1]50th percentile (median): half of the scores lie below the median, and half lie above the median.
[2]75th percentile: value at which 25% of the scores lie above that value and 75% of the scores lie below that value.

There was a weak, positive, and statistically significant correlation (r = 0.18–0.32) between the EI subscales, indicating that applicants who performed well on one subscale also performed well on the others. Furthermore, there was moderate to strong correlation between the subscales and total score, indicating that performing well on any subscale also indicated good overall performance on the EMI-T (Table 3).

Table 3. *Correlations between EI Subscales and Total Score*

Subscales	Perception and understanding of emotions	Acceptance of emotions	Management of emotions	Social awareness and relations	Total score
***Perception and understanding of emotions**	1.00[e]	0.22[b]	0.18[b]	0.20[b]	0.74[d]
Acceptance of emotions		1.00[e]	0.30[b]	0.30[b]	0.65[c]
Management of emotions			1.00[e]	0.32[b]	0.60[c]
Social awareness and relations				1.00[e]	0.62[c]

[a]0.00–0.10 Negligible correlation [b]0.10–0.39 Weak correlation [c]0.40–0.69 Moderate correlation [d]0.70–0.89 Strong correlation [e]0.90–1.00 Very strong correlation (Schober, Boer and Schwarte 2018)
All correlations statistically significant $p < 0.05$
*The correlations between subscales are not completely comparable; thus, the perception-and-understanding-of-emotions subscale's maximum score is 8 points, whereas the other subscales have a maximum score of 4 points.

Factors related to Social Care and Healthcare Applicants' Emotional Intelligence

All the demographic factors except participation in a preparation course had statistically significant relationships with an applicant's EI. (Table 4). The applicants

who were older, female, had a high school or higher education as a previous education and were born in Finland had higher EI scores. An applicant's parents being employed or born in Finland was also related to a higher EI score (Table 4).

Table 4. *Factors related to Social Care and Healthcare Applicants' EI*[a]

Factors related to EI total scores	Difference between means	95% confidence interval	p-value[b]
Age (years)			
Over 29 versus under 20	0.3188	0.0517 – 0.5859	0.012
Over 29 versus 20–24	0.3382	0.1323 – 0.5441	0.001
Gender			
Female versus male	0.7323	0.5711 – 0.8934	0.001
Previous education			
Vocational school versus high school	-0.5247	-0.7071 – -0.3424	0.001
Higher education versus high school	0.5109	0.2076 – 0.8141	0.001
Other education versus high school	-1.0385	-1.3883 – -0.6888	0.001
Higher education versus vocational school	1.0356	0.7295 – 1.3417	0.001
Other education versus vocational school	-0.5138	-0.866 – -0.1616	0.001
Other education versus higher education	-1.5494	-1.9769 – -1.1219	0.001
Place of birth			
Another country versus Finland	-2.7179	-2.9638 – -2.472	0.001
Parents' place of birth			
Finland versus another country	0.6829	0.5347 – 0.8311	0.001
Father's employment status			
Students versus self-employed persons	-2.1957	-3.4551 – -0.9363	0.001
Unemployed versus self-employed persons	-0.9564	-1.5211– -0.3917	0.001
Students versus upper-level employees	-2.3381	-3.6047 – -1.0715	0.001
Unemployed versus upper-level employees	-1.0988	-1.6794 – -0.5182	0.001
Students versus lower-level employees	-2.2773	-3.5384 – -1.0163	0.001
Unemployed versus lower-level employees	-1.0381	-1.6064 – -0.4697	0.001
Students versus manual workers	-2.1746	-3.425 – -0.9242	0.001
Unemployed versus manual workers	-0.9354	-1.4797 – -0.391	0.001
Pensioners versus students	2.0287	0.7541 – 3.3034	0.001
Unemployed versus pensioners	-0.7894	-1.387 – -0.1915	0.002
Mother's employment status			
Students versus self-employed persons	-1.2171	-2.1109 – -0.3233	0.001
Unemployed versus Self-employed persons	-1.138	-1.6953 – -0.5806	0.001
Students versus upper-level employees	-1.3126	-2.1976 – -0.4276	0.001
Unemployed versus upper-level employees	-1.2335	-1.7766 – -0.6904	0.001
Students versus lower-level employees	-1.266	-2.119 – -0.413	0.001
Unemployed versus lower-level employees	-1.1869	-1.6761 – -0.6976	0.001
Students versus manual workers	-1.2108	-2.0552 – -0.3663	0.001
Unemployed versus manual workers	-1.1316	-1.6057 – -0.6575	0.001
Pensioners versus students	1.018	0.1258 – 1.9102	0.014
Unemployed versus pensioners	-0.9389	-1.4937 – -0.3842	0.001
Participation in the preparation course			
Yes versus no	-0.0816	-0.2847 – 0.1216	NS

[a]total EI scores (EMI-T test) as a dependent variable (Tukey's test in post-hoc multiple group comparisons).

A regression analysis was also performed to analyse the degree to which the various factors explain the variation in social care and healthcare applicants' EI scores. Parents' working status was not included in the regression analysis, due to small sample sizes in some subgroups and participation in a preparation course was not included, because it was not statistically significantly related to the applicants' EI (Table 5).

According to the results all variables (age, gender, previous education, place of birth) were related to applicants EI but, accounted only for 14% of the variation in EI (R2 = 0.141, adjusted R2 0.139), indicating that these factors poorly explain the applicants' EI. (Table 5.)

Table 5. *Regression Model for Factors explaining Social Care and Healthcare Applicants' EI Variation*[a]

Factors explaining total EI scores	**Coefficient**	**SE**	**t**	**95% confidence interval** lower – upper bound	**p-value**
Age (years)					
Age 20–24 versus under 20	0.1843	0.090	2.049	0.008 – 0.361	0.041
Age 25–29 versus under 20	0.4678	0.108	4.341	0.257 – 0.679	0.000
Age over 29 versus under 20	0.7116	0.099	7.166	0.517 – 0.906	0.000
Gender					
Female versus male	0.5770	0.074	7.843	0.433 – 0.721	0.000
Previous education					
Vocational school versus high school	-0.6332	0.068	-9.290	-0.767 – -0.500	0,000
Higher education versus high school	0.1473	0.115	1.285	-0.077 – 0.372	NS
Other education versus high school	-0.6853	0.125	-5.477	-0.931 – -0.440	0.000
Place of birth					
Another country versus Finland	-2.4691	0.124	-19.912	-2.712 – -2.226	0.000
Parents' place of birth					
Finland versus another country	0.2256	0.071	3.193	0.087 – 0.364	0.001

[a] Multiple linear regression analysis with categorical variables
Coefficient = regression coefficient (Beta), SE = standard error, p-value = sig (two-tailed), confidence interval = 95% confidence interval level for regression coefficient

Discussion

This study aimed to assess undergraduate social care and healthcare applicants' EI and the factors related to it. According to the results, social care and healthcare applicants had EI scores above the centre of the score range. Thus, they performed well on the EI section of the UAS Exam and all EI subscales, indicating that the applicants already had EI abilities during the application phase. Previous studies have indicated that social care and healthcare applicants have better-than-average EI (Joseph et al. 2015, Štiglic et al. 2018, Stanley and Mettilda 2021). One explanation of this result may be that good EI abilities inspire individuals to select social care and healthcare as a career choice. This can be exploited in social care and healthcare student recruitment. Higher education institutions can emphasise that EI abilities are

required in these professions and, thus, can recommend social care and healthcare sector as a good career choice for applicants with high EI. In this study one reason for the applicants' good performance may also be the difficulty level (i.e. most of the items were easy) of the test used (EMI-T).

In this study, the applicants seemed to perform best in the management of emotions, indicating that they understand how to manage emotions and have the emotional flexibility needed to function appropriately in emotional situations. The applicants seemed to perform least well in the perception and understanding of emotions, indicating that they had difficulties recognising others' non-verbally transmitted emotions and understanding individuals' emotions and emotional reactions in various situations. Previous studies researching EI in healthcare student selection have mainly evaluated applicants' total EI scores, but not the EI subscales scores (Pienimaa et al. 2022a). However, Talman et al. (2020) also indicate that nursing applicants scored better in the management of emotions than in the perception of emotions, confirming the results of this study. Institutions of higher education should provide opportunities and interventions that enhance EI during education so that students who have difficulties with EI can be supported. Furthermore, information about an applicant's performance on various subscales can be used in the further development of the EMI-T on the subscale level. Those subscales that proved to be the easiest should be further developed, and their difficulty levels should be increased.

In our study, female gender, older age, a high school or higher education as previous education and an applicant's and their parents' having been born in Finland had positive relationships with EI scores obtained during student selection. Our results are in line with previous studies in which older age, a higher educational level (Talman et al. 2020) and female gender have been found to have positive relationships with EI among healthcare applicants (Carrothers et al. 2000, Talman et al. 2020). Perhaps increased cognitive ability and life experience facilitate emotional functioning, and education stimulates situations where emotional intelligence can be enhanced. Furthermore, female tend to have more nurturing role in societies and perhaps they also value more emotional aspects than males do and thus, have more experience and enter emotional interaction situation. This knowledge about the factors affecting EI in student selection is important because EI has an impact on study success (Pienimaa et al. 2022a). This information can be used in finding those applicants who may need more support to finish their studies successfully.

However, in this study these demographic factors only minorly (14% altogether) explained the variation in social care and healthcare applicants' EI indicating that factors such as gender, age and previous education as single factors do not explain the EI variation in the student selection context or affect the results of the EMI-T. Furthermore, socio-economic factors and cultural factors (such as place of birth) had only minor effects on the applicants' emotional intelligence. Thus, these results may indicate that EMI-T as a test does not discriminate against applicants from different cultures. Furthermore, EMI-T includes similar categories as validated EI instruments that have widely been used internationally in different target populations. Therefore, the use of EMI-T may be feasible in other populations. However, language and cultural validation are recommended in the future. The results of this study also imply that there are still several unknown factors affecting the EI during student selection.

Further research is needed, as there currently are only few studies that have researched EI in the student selection context (Arora et al. 2010; Pienimaa et al. 2022a) and the previous literature comparing various demographic factors and EI have had controversial results. Especially, studies that investigate the interactions between several factors and EI using regression analysis are needed. Previously, the research has focused on investigating only a few factors' interactions with EI (Fernández-Berrocal et al. 2012, Cabello et al. 2016).

Strengths and Limitations

The sample size was large, enabling the relevant statistical analysis. Furthermore, the sample was collected nationwide from all the UASs offering social care and healthcare degrees. The data were collected from a digital entrance examination system. This reduced the possibility of bias because there was no manual data collection. The high total scores reported in this study may be explained by the fact that the EMI-T has previously proven to be relatively easy (Pienimaa et al. 2022b). However, previous studies, indicate that social care and healthcare students have better-than-average EI scores. Although, the EMI-T has been developed and validated to the social care and healthcare student selection context, the content and items of the EMI-T are not social care and healthcare specific. Furthermore, the EI main categories of EMI-T are very similar to the categories of the previous EI instruments, which are validated internationally to several different target populations. Therefore, the use of EMI-T is possible in other target populations and situations such as in student selection in other student groups (e.g. medical or psychological field). However, the validation of the EMI-T to these other target populations and situations should be performed before the deployment.

Conclusions

Undergraduate social care and healthcare applicants managed overall well in EMI-T. Several demographic factors seem to influence EI. However, these factors, together only partially explained the variation in the applicants' EI. This indicates that these factors do not have a major effect on the EI scores obtained during student selection. Theoretical implications of the study suggest that as in previous studies age, gender and previous education have relationships with EI. However, these results also imply that there are still several unknown factors affecting the EI during student selection. Practical implications of the study indicate that social care and healthcare applicants have EI abilities needed to success in their studies and fair student selection is possible using the EMI-T. The future social care and healthcare research should focus on addressing EI in the student selection context and establishing which factors affect EI variation in this context.

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Psychological Determinants of Digital Health Literacy among Older Adults in Nigeria: A Cross-Sectional Study

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Digital health literacy (DHL) is increasingly essential for effective engagement with contemporary healthcare systems. Despite increasing digitilisation of health services, older adults, who typically require greater healthcare needs, remain disproportionately disadvantaged. While structural barriers have been widely examined, less attention has been given to psychological determinants of DHL. This study examined psychological determinants of digital health literacy among older adults in Ondo Town, Nigeria. A cross-sectional survey design was employed. A total of 258 older adults aged ≥ 60 years (mean=65.0, SD =3.7) were recruited from a State-owned hospital in Ondo town, Nigeria. Participants completed Digital Health Literacy Instrument (DHLI), the Multidimensional Health Locus of Control (MHLC) Scale, the General Self-Efficacy Scale (GSES), and a self-structured questionnaire on Attitude toward Digital Health Literacy. Multiple regression analysis revealed that psychological factors jointly explained 28.9% of the variance in DHL (adjusted R^2=.289, F(4,253) =27.06, p<.001). Attitudes toward digital health technology emerged as the strongest unique predictor (β=.335, p<.001), followed by self-efficacy (β=.214, p<.001) and internal health locus of control (β=.189, p<.001). External locus of control was not statistically significant (β=-.097, p=.076). These findings emphasize the need for interventions that aimed at improving digital health literacy among older adults, strategies to foster positive attitudes, build self-efficacy through hands-on experience and social support and as well strengthen internal health locus of control through empowerment-based education.

Keywords: *digital health literacy, attitudes, self-efficacy, health locus of control, older adults*

Introduction

The present evolution of digital technology has transformed domains of human life, with healthcare inclusive, by enhancing easy access and efficient delivery of health services. The emergence of digital health resources which include mobile health applications, online portals, telemedicine services and wearable technologies offer unprecedented opportunities for individuals and communities to maintain maximum well-being more proactively (WHO 2020, Crawford & Serhal 2022). These technologies have been shown to facilitate patients' participation, enhance self-care and healthy lifestyles (Van der Mispel et al. 2017). However, the benefits of these advancements are unevenly distributed, as digital health literacy (DHL), defined as the capability to search, understand and appraise health information from electronic

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sources to make informed health decisions (Norman & Skinner 2006), remains uneven, particularly among older adults in Nigeria. Older adults often report fears about complex functionalities of smart devices and digital interfaces, leading to hesitation or avoidance of digital health tools (Ezeudoka & Fan 2024). Yet, this unique older adult population stand to benefit most from digital health innovations due to their frail health conditions, frequent use of health services and health-related information needs (Chesser et al. 2016, Neter & Brainin 2012). As such, examining the psychological factors that influence DHL among older adults in Nigeria is critical to bridging existing gaps and fostering health equity in this digital era.

DHL is a subset of general health literacy that focuses on extent to which an individual has the capacity to interact with digital health resources to make health informed decisions. According to Norman and Skinner (2006), DHL involves six core literacies which are traditional, health, information, scientific, media, and computer literacy. Higher level of DHL is associated with increased health knowledge, better self-care, and improved communication with healthcare providers (Paige et al. 2017), while lower level of DHL is associated with reluctance to engage with digital health services and not seeking health information from reliable digital sources (Fan et al. 2024), thus limiting the individual's access to essential health benefits.

In Nigeria, despite the increase in internet and smartphone penetration recently, internet penetration stood at approximately 45.5%, remains uneven, with rural areas significantly underserved (Kepios 2024). Poor broadband infrastructure, unstable power supply, existing service delivery, inadequate experienced health practitioners and insufficient integration of operational and cultural consideration necessary for scalable implementation exacerbate low digital health services (Aranda-Jan et al. 2014, Adebayo & Ofoegbu 2014). The effort made to initiate Nigeria's Digital Health Vision between 2015 -2020 to address these challenges has been slow and fraught with implementation and systemic issues (WHO 2020, Aririguzoh et al. 2021, Idoga & Toycan 2016).

DHL is immensely crucial, especially for the older adults to support autonomy and effective communication with healthcare providers (Van der Vaart & Drossaert 2017). A plethora of studies have demonstrated the significance of DHL and internet use in facilitating overall health of older adults (Wen et al. 2023, Schoeppe et al. 2016). Despite its efficacy, research reveals a digital divide among older populations due to age-related changes which include sensory deficit, decreased motor abilities, and cognitive decline, lower levels of education and limited digital experience and habits (Kontos et al. 2014, Heart & Kalderon 2013). Research indicates that older adults can develop digital competence when provided with needed guidance and motivation to enhance their integration in the present digital age (Kim 2015). Identifying psychological factors that underlie the involvement of older adults' digital health resources is essential for designing inclusive interventions and promoting their integration into the digital health ecosystem. Among these psychological factors are attitudes, health locus of control (HLC), and self-efficacy.

Attitude, as a psychological factor, represents an individual's predisposition toward particular behaviours or technologies. Attitudes influence motivation, willingness to learn and openness to new experiences, which can lead to the adoption of digital health resources among older adults. Attitudes toward digital health technology encompass

beliefs about its usefulness, perceived ease of use, safety, and trustworthiness (Or & Karsh 2009). Positive attitudes have been correlated with increased intention to use and actual use of digital health technologies among older adults (Heart & Kalderon 2013). Di Giacomo et al. (2020) indicated that positive experiences with electronic services can foster positive attitudes and future usage. Negative perception such as concerns about privacy, fear of technology, and skepticism toward online information often serve as barriers to DHL (Czaja et al. 2006). A recent scoping review by Shi et al. (2024) revealed that attitudes toward online health source of information greatly impacted older adults' DHL. Previous studies found that interest in application of internet, easy to use electronic gadgets and no pressure to use affected older adults' attitude toward DHL (Arcury et al. 2020, Price-Haywood et al. 2017, Cajita et al. 2017).

Health locus of control (HLC) is another psychological factor that plays a vital role in shaping health outcomes, including digital health information-seeking behaviour. HLC refers to individuals' beliefs regarding the extent to which their health is influenced by internal factors (e.g., personal actions), powerful others (e.g., doctors), or by chance/luck (Wallston et al. 1978). The individuals with a high internal HLC are more likely to proactively search for health information and engage in health preventive behaviours, and they are often self-directed learners who utilize online resources to manage their health effectively (Hairaty et al. 2019, Seçkin et al. 2016). Conversely, individuals with an external HLC (especially chance-based) may view health as outside their control, leading to reduced motivation to seek health information or adopt new technologies as they may rely on doctors or fate (Helmer et al. 2012). Research indicates a positive correlation between internal HLC and both general and DHL (Purcell 2021).

Self-efficacy, another key psychological construct, refers to individuals' beliefs in their capacity to execute behaviours necessary to produce particular outcomes (Bandura 1997), also plays a vital role in digital engagement. Digital self-efficacy encompasses confidence in application of electronic devices, navigating digital platforms and appraising online health information (Kim & Xie 2017). Studies have consistently shown that digital self-efficacy predict better DHL among older adults (Liu et al. 2023, Chung & Nahm 2015). Those with high digital self-efficacy are autonomous, adaptable and proactive in engaging with digital health resources (Luo et al. 2025, Korkmaz Aslan et al. 2021). Also, Liu et al. (2023) found that self-efficacy directly influenced health literacy and indirectly mediated the relationship between social support and health literacy.

With the evolution and transformation of digital health utilization and increased DHL worldwide, Nigeria, the most populous country in Africa exhibit relatively low levels of DHL, with significant disparities between urban and rural regions influenced by several factors (Babalola et al. 2019). While there is growing public interest in digital health services, particularly among younger populations, older adults remain at a distinct disadvantage (Aririguzoh, et al. 2021). Previous studies have shown that while patients generally expressed their interest toward digital health adoption, structural and economic barriers limit their use (Onumajuru et al. 2024, Itanyi et al. 2023, Olamoyegun et al. 2020). Similarly, healthcare professionals in Nigeria exhibited varied attitudes toward digital integration, often constrained by systemic and knowledge-related issues (Onumajuru et al. 2024, Ojo et al. 2022). Therefore, examining the psychological determinants of digital health literacy in older Nigerian adults is essential to developing

age-sensitive digital health strategies and promoting health equity in this digital era. This study hypothesized that:

1. Psychological factors of attitudes towards digital health technology, health locus of control and self-efficacy will jointly determine DHL among older adults in Ondo Town, Nigeria.
2. Psychological factors of attitudes towards digital health technology, health locus of control and self-efficacy will independently determine DHL among older adults in Ondo Town, Nigeria.

Methods

Participants

This study employed a cross-sectional quantitative survey method. A total of 258 (male =90; female =168) older adults aged 60 years and above (mean = 65.0, SD = 3.7), who resides in Ondo town, possessing basic literacy in English or a local Nigerian language, attending a State-owned hospital in Ondo, South-west, Nigeria and showed willingness to participate voluntarily were recruited for the study. Convenient sampling technique was employed to select the participants for the study. Purposive sampling technique was also utilized to recruit individuals, who have not travelled abroad before (especially to developed nations) who could have been well-exposed to compulsory utilization of advanced health digital tools.

Measures

Digital Health Literacy Instrument (DHLI)

The Digital Health Literacy Instrument (DHLI), developed by van der Vaart and Drossaert (2017), was employed to evaluate respondents' digital health literacy levels. The DHLI comprises seven skill domains, assessed through 21 self-reported items and 7 performance-based items, encompassing: (1) operational skills, (2) navigation skills, (3) information searching, (4) evaluating reliability, (5) determining relevance, (6) content creation, and (7) privacy protection. Illustrative items include: "How easy or difficult is it for you to use buttons, links, and hyperlinks on websites?" and "When searching the Internet for health-related information, how easy or difficult is it for you to make a selection from the available options?" Self-report items required participants to rate the perceived difficulty of specific tasks and the frequency with which they encountered internet-related challenges. Responses were captured using a 4-point Likert scale, ranging from "very easy" to "very difficult" and from "never" to "often." All item scores were reverse-coded such that higher scores indicated greater levels of digital health literacy. In this present study, DHLI demonstrated Cronbach alpha coefficients of .81.

Attitudes toward Digital Health Literacy

A self-structured questionnaire of 15-items based on constructs from the Technology Acceptance Model (TAM) (e.g., perceived usefulness, perceived ease of use, attitude toward use, behavioural intention to use and actual use), was used to assess the participants' attitudes toward digital health literacy. Examples of the items include, "digital health tools help me to access health information more quickly" "interacting with digital health platforms does not require a lot of mental effort" and "I like the idea of using digital health tools to monitor my health. The questionnaire is rated on a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). The questionnaire demonstrated acceptable internal consistency of Cronbach alpha .79.

Multidimensional Health Locus of control (MHLC) Form A

Health locus of control of the participants was assessed using MHLC scale Form A developed by Wallston et al. (1978). The beliefs of the older adults about internality, chance and powerful others in relation to health outcomes were assessed. The scale consists of 18-items questionnaire classified into three subscales with six items each: internal (e.g., If I get sick, it is my own behaviour which determines how soon I get well again), powerful others (e.g., having regular contact with my physician is the best way for me to avoid illness) and chance (e.g., Luck plays a big part in determining how soon I will recover from an illness). The items under powerful others and chance subscales were collapsed to be external health locus of control. The scale is rated on a 6-point Likert scale, which ranges from strongly disagree (1) to strongly agree (6). MHLC demonstrated internal consistency of Cronbach alpha .84 and .77 for both internal and external health locus of control respectively.

General Self-Efficacy Scale (GSES)

Participants' self-efficacy beliefs were assessed using the General Self-Efficacy Scale (GSES), a 10-item instrument developed by Schwarzer and Jerusalem (1995). The GSES utilizes a 4-point Likert scale, with response options ranging from "Not at all true" (scored as 1) to "Exactly true" (scored as 4). Total scores range from 10 to 40, with higher scores indicating higher self-efficacy. The scale demonstrated internal consistency of Cronbach alpha .87.

Procedure

Upon research ethical approval from the first author's institution, permission to conduct the study was sought from the authorities of the State-owned hospital used to have access to the participants, after which data were collected on different occasions with the supports of the authorities. Data were collected within four weeks of patients' patronage to the hospital from September to October 2025. Administration

of questionnaire was conducted via online Google Form and paper filling. 217 older adults completed the online Google Form while 41 completed the paper form questionnaire. Participation was voluntary. The response to the questionnaire was about 20-25 minutes.

Data Analysis

Descriptive statistics frequency count, percentage, mean and standard deviation were employed to summarize demographic results, while multiple regression analysis was utilized to examine the psychological determinants of DHL. All analyses were performed using Statistical Package for Social Sciences (SPSS) (version 26.0, IBM, New York, US). Statistical significance was set at $p < .05$.

Results

Table 1. *Demographic Characteristics of the Respondents*

Variable		**Frequency**	**Percentage**
Gender	Female	168	65.1
	Male	90	34.9
Age	Mean = 65 ± 3.7		
Highest Level of Education	No Formal Education	2	.8
	Primary	6	2.3
	Secondary School	23	8.9
	Tertiary	172	66.7
	Master	37	14.3
	PhD	18	7
Frequency of Internet usage	Never	6	2.3
	Several days a week	54	20.9
	Every day	198	76.7
Mean of Internet Access	Mobile phone	234	90.7
	Laptop	24	9.3

Table 1 presents the demographic characteristics of 258 older adults (aged 65 and above) in Ondo, Nigeria. From Table 1, it can be seen that most of the respondents were older adult women making up nearly two-thirds (65.1%) compared to just over a third (34.9%) who were men. Based on the educational level of the respondents, the vast majority had tertiary education (66.7%), with additional representation at postgraduate levels (Master's; 14.3%; PhD: 7%). Very few participants reported low educational attainment (no formal education: 0.8%; primary: 2.3%). Internet use among the respondents was very high. Over three-quarters (76.7%) reported daily use of internet and another 20.9% reported using it several days a week. Only a very small minority (2.3%) never used it. Mobile phone was reported as the dominant device for accessing the internet by an overwhelming 90.7% of the respondents. While 9.3% reported using laptops

Table 2. *Results of Multiple Regression on Joint Contribution of Psychological Factors on Digital Health Literacy among Older Adults*

R = .547 Adj R^2 = .289 R^2 = .300 Std. Error = 5.41						
Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	3169.969	4	792.492	27.056	.000[b]
	Residual	7410.682	253	29.291		
	Total	10580.651	257			

As shown in the Table 2, the joint contribution model showed that the psychological factors (attitudes towards digital health technology, health locus of control (internal and external) and self-efficacy) jointly had a significant impact on DHL; $F(4,253) = 27.06$, $p < .001$. The adjusted R^2 of .289 showed that after adjusting for the number of predictors and sample size, the model accounted for 28.9% variance in DHL. Variables accounting for the remaining variance were not included in this study. This implies that there was a significant joint contribution of psychological factors on digital health literacy among older adults.

Table 3. *Results of Multiple Regression on Relative Contribution of Psychological Factors of Attitudes towards Digital Health Technology (ATDHT), Health Locus of Control (Internal and External) and Self-Efficacy on Digital Health Literacy among Older Adults*

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
	(Constant)	17.474	3.025		5.777	.000
	ATDHL	.237	.042	.335	5.685	.000
	Internal LOC	.208	.064	.189	3.271	.001
	External LOC	-.075	.042	-.097	-1.783	.076
	Self-efficacy	.301	.083	.214	3.638	.000
a. Dependent Variable: DHL						

Table 3 presents the standardized coefficients, showing the relative contribution of each predictor to digital health literacy (DHL). Holding all other variables constant, attitude towards digital health technology (ATDHL) was the strongest predictor ($\beta = .335, p < .001$). The second strongest relative contributor was self-efficacy ($\beta = .214, p < .001$), followed by internal health locus of control ($\beta = .189, p = .001$). In contrast, external health locus of control did not make a statistically significant unique contribution ($\beta = -.097, p = .076$). This suggests that beliefs attributing health control to external factors, such as chance or powerful others, were not a significant independent predictor when the effects of attitudes, self-efficacy, and internal locus of control were accounted for. In summary, positive attitudes, greater self-efficacy, and a stronger internal locus of control each uniquely and positively determined digital health literacy, with attitudes being the most influential factor.

Discussion

The present study examined psychological determinants of digital health literacy among older adults. In addition, the study investigated both joint and relative contributions of selected psychological factors of attitudes towards digital health technology (ATDHL), health locus of control (internal and external) and self-efficacy on digital health literacy among older adults. The results revealed that selected psychological factors jointly exerted a statistically significant influence on digital health literacy. This indicates important role of psychological characteristics in determining how older adults engage with digital health resources. This result aligns with existing literature that emphasize the multidimensional nature of digital health engagement. Prior research has consistently highlighted that positive attitude towards technology, a sense of personal control over health and confidence in one's digital abilities are critical enablers of health-related technology use among older populations (Kim & Xie, 2017, Heart & Kalderon 2013). Our results extend these findings to the Nigerian setting, where digital infrastructure and literacy remain uneven (Kepios 2024, Aririguzoh et al. 2021).

Moreover, the study found that attitude toward digital health technology, self-efficacy and internal locus of control each uniquely and positively predicted digital health literacy among older adults, with attitudes being the most influential factor in this present study. That is, older adults who held more positive attitudes toward digital health devices as beneficial, accessible and trustworthy demonstrated significantly higher levels of DHL. This finding corroborates the previous findings by Price-Haywood et al. (2017), Heart and Kalderon (2013) that positive attitudes have shown to predict not only initial adoption but also sustained engagement with digital health platforms. Positive attitude can possibly function through intertwined factors. For instance, favourable perceptions can reduce psychological resistance, technophobia and anxiety associated with digital technologies. Also, attitudes can influence motivational orientation, shaping whether individuals perceive digital tools as empowering resources or intimidating obstacles. In addition, attitude can affect learning behaviour, as individuals are more interested to training and learning skill acquisition opportunities. Though prior study by Ezeudoka and Fan (2024) indicated that, older adults were particularly susceptible to technophobia, skepticism toward online information and concerns about data privacy and gadget complexity, leading to hesitation or avoidance of digital health tools. These negative perceptions are not unfounded; they revealed the genuine usability challenges encountered and a fail to accommodate age-related sensory and cognitive changes (Czaja et al. 2006). However, the present findings suggest such perceptions are not immutable. Di Giacomo et al. (2020) indicated that positive experiences with electronic services can foster more favourable positive attitudes and increase future usage intentions among older adults.

Internal locus of control was identified as a significant determinant of digital health literacy, indicating that beliefs regarding personal control over health outcomes influence digital health competencies. This result demonstrates that older adults who believe their health outcomes are largely contingent upon their own behaviours, decisions and efforts exhibit greater competence in engaging with digital health

resources. Similarly, older adults with stronger internal locus of control are more active in taking decisions that positively affect their well-being. Internal locus of control may foster intrinsic motivation for digital engagement which may indirectly serve as instrumental resources for self-management rather than optional conveniences. This corroborates with the findings of Purcell (2021) that stronger internal locus of control (belief that one controls their own health outcomes) is significantly related to higher electronic health literacy, positive attitudes towards healthcare providers, higher trust in physicians and medication adherence. It was added that internal locus of control act as a significant mediator between electronic health literacy and key patient outcomes. Similarly, Seçkin et al. (2016) indicated that individuals with stronger internal locus of control beliefs were more likely to actively seek and critically assess online health information and as well utilize electronic health resources as mechanisms of self-regulation.

In contrast, external locus of control did not demonstrate a statistically significant independent contribution to DHL when controlling for other psychological variables. This finding suggests that attributing health outcomes to chance or powerful others such as healthcare providers does not independently determine digital health literacy among older adults in this present study. This finding is consistent with prior research indicating that external locus of control may be associated with passive health behaviours and reduce the motivation to seek health information independently (Helmer et al. 2012).

In addition, self-efficacy demonstrated a significant positive contribution to DHL. Older adults with higher self-efficacy were more likely to report greater competence in navigating digital platforms searching for health information and assessing online health contents. This is consistent with Bandura's (1997) assertion that individual's beliefs in their capabilities strongly influence their behavioural engagement and persistence when facing challenges. Digital health literacy inherently involves tasks that require confidence in surfing the internet by navigating unfamiliar systems, troubleshooting errors and interpreting complex information. This is in accordance with the finding of Liu et al. (2023) that self-efficacy has a significant positive relationship with health literacy which indicates that patients with higher self-efficacy tend to have higher health literacy. It was further found that self-efficacy mediated the relationship between social support and health literacy. Similarly, Luo et al. (2025) finding revealed a statistically significant positive relationship between self-efficacy and e-Health literacy among older adults. That is, older adults with higher self-efficacy tended to have higher e-Health literacy.

Limitations

While this study provides valuable insights into the psychological determinants of digital health literacy (DHL) among older adults in Ondo, Nigeria, several limitations should be acknowledged. First, the cross-sectional design employed in this study limits the ability to infer causal relationships between the psychological factors (attitudes, health locus of control and self-efficacy) and digital health literacy. Although significant associations were identified, the directionality of these

relationships cannot be definitively established. Longitudinal or experimental research is needed to determine whether changes in these psychological constructs precede improvements in DHL.

Second, the study relied on self-reported measures, which may be subject to social desirability bias, recall bias, or overestimation of digital competencies. Participants may have provided responses they perceived as favourable or may have inaccurately assessed their own digital skills. Future studies should consider incorporating objective assessments or performance-based tasks to complement self-report data. Third, the sample was drawn from a single State-owned hospital in Ondo town, using a convenient sampling technique and also excluded individuals who had travelled abroad. This may limit the representativeness and generalizability of the findings to older adults in other regions of Nigeria, particularly those in rural or underserved areas with limited access to digital infrastructure.

Lastly, the use of a self-developed scale to assess attitudes toward digital health technology, although demonstrating acceptable internal consistency, this has only been used in this study. This could affect the comparability of findings across studies. Future research should consider using standardized validated instruments.

Conclusion

This study examined the psychological determinants of digital health literacy among older adults in Ondo, Nigeria, focusing on attitudes toward digital health technology, health locus of control (internal and external), and self-efficacy. The findings revealed that these psychological factors jointly and significantly predicted digital health literacy. Specifically, attitudes toward digital health technology emerged as the strongest predictor, followed by self-efficacy and internal health locus of control. In contrast, external health locus of control did not make a statistically significant unique contribution to DHL. These results emphasize the importance of addressing psychological readiness in efforts to enhance digital health literacy among older adults. Positive attitudes toward digital tools, confidence in one's ability to use them, and a sense of personal control over health outcomes are key drivers of engagement with digital health resources. Interventions aimed at improving digital health literacy among older adults should go beyond basic digital skills training. Strategies that foster positive attitudes, build self-efficacy through hands-on experience and social support, and strengthen internal health locus of control should be designed and incorporated into health programmes. Health policymakers and programme designers should consider these psychological dimensions when developing inclusive digital health strategies tailored to the needs of aging populations.

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