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# Transparency and Trustworthiness in User Intentions to Follow Career Recommendations from a Learning Analytics Tool

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**Abstract**

Transparency and trustworthiness are among the key requirements for the ethical use of learning analytics (LA) and artificial intelligence (AI) in the context of social inclusion and equity. However, research on these issues pertaining to users is lacking, leaving it unclear as to how transparent and trustworthy current LA tools are for their users and how perceptions of these variables relate to user behaviour. In this study, we investigate user experiences of an LA tool in the context of career guidance, which plays a crucial role in supporting nonlinear career pathways for individuals. We review the ethical challenges of big data, AI, and LA in connection to career guidance and analyze the user experiences ($N$ = 106) of the LA career guidance tool, which recommends study programs and institutions to users. Results indicate that the LA career guidance tool was evaluated as trustworthy but not transparent. Accuracy was found to be a stronger predictor for the intention to follow on the recommendations of the LA guidance tool than was understanding the origins of the recommendation. The user's age emerged as an important factor in their assessment of transparency. We discuss the implications of these findings and suggest emphasizing accuracy in the development of LA tools for career guidance.

**Notes for Practice**

- We investigate transparency as a multidimensional construct in the context of AI enhanced LA for career guidance.
- Users perceive guidance from the LA tool as more trustworthy but less transparent. The user's age plays an important role in evaluating transparency.
- Trustworthy guidance tools require the development of qualitative dimensions, including accuracy and a clear basis for the recommendations.
- Accuracy is vital for users in forming intentions to follow LA career guidance recommendations. However, users might follow the provided recommendations even if their basis is not clear to them.
- Concern is raised about users overtrusting AI enhanced LA guidance.

**Keywords**

Artificial intelligence, AI, learning analytics, career guidance, transparency, trustworthiness

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## 1. Introduction

Despite envisioning many positive consequences for individuals and societies, risks of various levels are foreseen with artificial intelligence (AI) in many important areas of life (European Commission, 2021). As an example of a high-risk use, the European Commission (2021) lists AI-assisted technology used in education or vocational training that might "determine the access to education and professional course of someone's life" (sec. 35). Classifying the use of AI technology for directing individual education and career paths as "high risk" does not mean that research, development, or implementation are prevented, but that the associated risks must be understood and mitigated. AI-based career guidance might similarly be used to determine someone's professional life direction and thus contribute to the state of inequity in society. Accordingly, such tools should be subject to high ethical standards and transparency requirements to facilitate human trust and successful utilization. However, the current research literature does not provide enough insight into user experiences of transparency and trustworthiness regarding technologies aiming to direct human life paths. The interplay of transparency and trustworthiness and their impact on user intentions to change their career pathways based on advice from emerging technology are left unclear.

In this study, we investigated user perceptions of a learning analytics (LA) career proof-of-concept guidance tool, providing recommendations to users about study programs and institutions. We aimed to discover several things: 1) to better understand how transparent these services were to their users; 2) to gauge how trustworthy they were seen to be; 3) to measure the extent to which users intended to follow the recommendations they were given; and 4) to analyze how these perceptions interplayed with each other. More broadly, this study contributes to a better understanding of how individuals can discover and enter career paths in an ethically sound way with the support of emerging technologies.

### 1.1. Previous Research on Computer-Supported Career Guidance

Career guidance is a lifelong process that enables individuals to identify their interest and capabilities, to make educational and occupational decisions, and to manage their individual life paths (Council of the European Union, 2008). This process is heavily intertwined with technology (Osborn et al., 2014), which has been researched and utilized in practice for many years as computer-assisted career guidance, computer-based career planning (Harris-Bowlsbey, 2013), and other technology-related terms (Kettunen, 2017). Use of career guidance technology has been positively linked to various career-related indicators such as retention in education (Stephen, 2010), career decidedness (Betz & Borgen, 2009), career readiness (Chen et al., 2022), sense of control in career decision-making (Maples & Luzzo, 2005), career-related metacognition (Osborn et al., 2021), and career decision-making self-efficacy (Tirpak & Schlosser, 2013).

Despite many benefits, several ethical issues of using computer-assisted career guidance tools have been recognized. Concerns about the overly strong influence of digital tools and a "black box paradox" were raised in the early development of digital career guidance tools in the 1970s (as recollected by Harris-Bowlsbey & Samson, 2011). Issues of poor data timeliness and quality, intentionally/unintentionally biased or discriminatory career information, confidentiality, unequal access, lack of contextual information, and inadequate user competence to use such tools have all been raised (Sampson & Makela, 2014; Sampson et al., 2018, 2020). The recommendations for using computer-assisted career guidance tools also acknowledge the importance of understanding and introducing technological limitations to the users (Copeland et al., 2011).

However, the expressed ethical concerns and formulated recommendations have been examined empirically only to a limited extent. The influence of the provided information and the extent to which guidance tools act as independent agents in career guidance is unclear. For example, Gati and Kulcsár (2021) have expressed the need to implement AI in career guidance, but little is known about how users will perceive their interactions with AI, how recommendations will be understood, and how they will affect the individual's career decisions. For instance, Gati and Asher (2001) found that users tend to over focus on the final recommendations provided by the digital guidance tool, to a large extent ignoring other aspects of the career advice. Critical approaches on the use of technology in guidance are scarce and focus primarily on surveillance concerns (Staunton, 2020). The issue of user perceptions of transparency and trustworthiness of career guidance technologies, and their intentions to adjust their life directions according to the algorithmic suggestions, need further examination. So far, we have only limited understanding about the possible impact of these emerging tools on users and on society at large.

### 1.2. AI-Enhanced LA Tools for Career Guidance

LA refers to the measurement, collection, analysis, and reporting of data about learners and their contexts (Siemens, 2013). In this process, LA can rely on AI methods for collection and analysis of learner data and for production of more accurate results (Ez-Zaouia & Lavoué, 2017). Meanwhile, AI is not a single method but a variety of subfields aiming to "perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving" (Baker & Smith, 2019, p. 10). The most notable subfields of AI are machine learning, natural language processing, and deep learning (Zawacki-Richter et al., 2019). In this regard, LA tools powered by AI might capture and process data from learners and their environments, and ultimately, produce personalized outputs. More specifically, such tools might present and visualize collected personal data about various aspects of a user's life, such as habits and interests.

Career guidance can also be considered a learning process building on past experiences, including information on the self and the world, with the goal of making decisions and finding pathways in education and work towards desired future outcomes. Therefore, LA tools can utilize an individual's information and learning data for guidance purposes. This process could be further optimized by considering individual needs and preferences. Although the use of LA tools is becoming widespread in educational institutions, and has been used to support guidance through certain shorter periods of the institutionalized academic journey (De Laet et al., 2020; Guerra et al., 2020; Gutiérrez et al., 2020), the use of LA as a career guidance support tool remains underexplored. A gap of scientific literature in the area of emerging technologies for career guidance is produced by the general decrease of research on computer-assisted career guidance, which has continued for several decades (Offer & Samson, 1999). The development of digital guidance tools has, on the contrary, continued to grow. Currently guidance tools range from recommending learning materials and tasks within a course (Drachsler et al., 2015) to recommending study programs (Baneres & Conesa, 2017), suitable faculties (Kamal et al., 2020), study places (Rivera et al., 2018), occupation (Ochirbat et al., 2018), short- and long-term career goals (Alkan et al., 2019), and suitable jobs (Gutiérrez et al., 2019). Recommendations of different sorts seem to remain a preferred way to provide individuals with career direction; however, research on user experience remains scarce. So far, research on user experiences with career guidance services primarily focused on usability and satisfaction issues, leaving it unclear as to what kind of understanding users have about the origin of the provided recommendations, if they regard them as trustworthy, and to what extent they follow them.

Recent investigation into AI-supported guidance indicates that higher education students and guidance professionals expect AI primarily to support career planning through decision support, matching individuals with counsellors and tracking their discussions, recognizing skills, identifying existing skill gaps based on profile data, and collecting information on the student for guidance staff in an institution (Westman et al., 2021). Khare et al. (2018) envision a comprehensive career guidance system in higher education institutions. The system would start by gathering data about interests and historical performance to suggest study programs for prospective students. It would then continue to suggest possible courses and extra-curricular activities for enrolled students, as well as jobs and volunteering opportunities based on their study results. By the end of their studies, the system would use academic records to support their decisions of whether and what education to continue or recommend possible pathways to jobs (Khare et al., 2018). Westman et al. (2021) also describe several possible functioning modes of AI in career guidance ranging from using AI as a tool for guidance tasks, AI as an assistant, AI as a collaborator, and finally AI as a coach providing virtual guidance for a student's educational and career choices throughout their entire lives.

The wide variety of existing career guidance tools and the envisioned uses of AI guidance suggest a growing prevalence of career guidance technology, evolving from a tool to an active party in the guidance process. AI is expected to develop to be fully integrated throughout the private and institutional domains, providing personalized recommendations for all educational and career-related decisions throughout the life of an individual. The growing agency of AI tools requires more trust to be placed in them, suggesting the growing vulnerability of their user. Thus, empirical exploration is needed regarding the positive and negative views users have when they rely on emerging technologies for career advice. If individuals perceive career guidance technology as trustworthy, do they understand the functioning of these tools, and how much do they intend to follow the given recommendations? In the next section, we review studies from the fields of AI, LA, and recommendation systems in connection to transparency, trustworthiness, and trust.

### 1.3. User Perceptions of Transparency

Transparency requirements for technology and personal data use are firmly established in the European Union (High-Level Expert Group on AI, 2019; General Data Protection Regulation, 2016). According to this legal framework, individuals should have information about the complete lifecycle of their personal data: What data is being gathered, how it is being used, by whom, for what purposes, and for how long. Transparency is also seen to be at the heart of development and deployment of ethical LA tools (Pardo & Siemens, 2014) and is often the value focus of the field (Hakami & Hernández-Leo, 2020). Research literature so far has not offered a unanimous operationalization of transparency, but the definitions vary across studies and domains (Zheng & Toribio, 2021). Generally, transparency can be understood as "the quality that makes something obvious or easy to understand" (Merriam-Webster Dictionary, n.d.) or "the quality of being done in an open way without secrets" (Cambridge Dictionary, n.d.). Schnackenberg and Tomlinson (2016) suggested a framework to better understand transparency in organizations as a multidimensional construct consisting of clarity, accuracy, and information disclosure. Clarity refers to the information being understandable and meaningful. Accuracy signifies that information is perceived as precise. Information disclosure is described as the availability of valuable information (Schnackenberg et al., 2021).

The definition of transparency also implies different requirements from various stakeholders (Winfield & Jirotka, 2017). For example, users might be satisfied with a rough understanding of the logic behind the digital tools they use, while developers or other stakeholders might require detailed information on their internal workings in order to inspect and improve them (Felzmann et al., 2019). In connection with recommendation systems, the main goal of transparency is to enable users to understand why certain recommendations were provided (Sinha & Swearingen, 2002). However, so far user perceptions of transparency, and its effect on users, are not completely understood (Felzmann et al., 2019). Some research shows that transparency is valued by users (Herlocker et al., 2000), and that transparency perceptions relate to trust (Schnackenberg et al., 2021; Shin, 2020) and acceptance of recommendations (Cramer et al., 2008). However, research on transparency shows mixed effects on users, and that tested tools, tasks, and contexts play a vital role in understanding transparency perceptions and their relation to trust (Felzmann et al., 2019). So far, we have not found studies exploring transparency in the context of career decisions and career guidance tools. Thus, to explore these dimensions of transparency from the user perspective, we formulated the following hypotheses:

H1: The perceived clarity dimension of transparency positively influences intentions to follow the career guidance recommendations.

H2: The perceived accuracy dimension of transparency positively influences intentions to follow the career guidance recommendations.

H3: The perceived information disclosure dimension of transparency positively influences intentions to follow the career guidance recommendations.

### 1.4. Human Trust in Technology

Human trust in technology has sparked wide interest with the rise of various applications of AI technology, such as robots, chatbots, virtual assistants, smart speakers, and recommendations systems (Felzmann et al., 2019). To address human trust in AI technology, it is worth looking at previous research on trust. Mayer et al. (1995) suggested a model for understanding trust in an organizational context, positioning trustworthiness as a characteristic of the party in question. Meanwhile, trust is defined as an individual's willingness to take risks and to be vulnerable. Accordingly, in the suggested model, perceived trustworthiness influences how much an individual is willing to take a risk and this in turn influences the actual risk taking (Mayer et al., 1995). Lee (2018) continued to specify that trust should be specifically understood in "situations characterized by uncertainty and vulnerability" (Lee, 2018, p. 4), which is also common for life situations when individuals are searching for guidance, including education and career guidance. We have, so far, not found studies examining trust in the field of digital guidance tools. However, Hong and Cho (2011) tested the model in the field of e-commerce and found that trustworthiness affects trust and behaviour intentions. Thus, trustworthiness as a characteristic of the digital tool in question and behaviour intentions to act upon that perceived trust should be differentiated, so we will investigate them separately in this paper. Additionally, transparency can increase a user's trust in personalized recommendations in the entertainment industry as suggested by Shin (2020). Following this line of thought, we hypothesized that the clarity, accuracy, and information disclosure dimensions of transparency predict trustworthiness, and trustworthiness in turn predicts user intentions in career guidance:

H4: The perceived clarity dimension of transparency positively influences the perceived trustworthiness of the career guidance recommendations.

H5: The perceived accuracy dimension of transparency positively influences the perceived trustworthiness of the career guidance recommendations.

H6: The perceived information disclosure dimension of transparency positively influences the perceived trustworthiness of the career guidance recommendations.

H7: Perceived trustworthiness influences intentions to follow the career guidance recommendations.

Trust in technology might also be affected by several intervening variables such as individual factors, tested algorithms, the task at hand, and the context (Mahmud et al., 2022). For example, in case of digital tools, perceived trustworthiness also relies on design elements and the appearance of the tool (Bøegh, 2014). Thus, it is important to explore and understand the use of algorithmic recommendations in a natural context with specific digital tools. The role of demographic variables is also often investigated in user experiences with algorithms. For instance, women have been shown to see algorithmic recommendations as less useful in the areas of media, justice, and health (Araujo et al., 2020). Previous research on career guidance has not shown any gender effects in computer-assisted career guidance use or effects (Seeger, 1988). However, men seem to seek information from more diverse sources (Mau, 1999). The evidence on age influence is mixed (Mahmud et al., 2022), with some studies showing negative perceived usefulness associated with age (Araujo et al., 2020). There is a need to better understand the role of these factors in perceptions of transparency, trustworthiness, and user intentions in the field of career recommendations, since career guidance services often target populations of a specific age. To understand the interrelationships between transparency, trustworthiness, user intentions, and user age in technology-supported career decision-making, we tested the following hypotheses:

H8a: User age influences the perceived clarity dimension of transparency.

H8b: User age influences the perceived accuracy dimension of transparency.

H8c: User age influences the perceived information disclosure dimension of transparency.

H8d: User age influences the perceived trustworthiness of the career guidance recommendations.

H8e: User age influences the intentions follow the career guidance recommendations.

### 1.5. Aims of This Research

In this research, we evaluated positive and negative user perceptions of common career guidance technology functionality, specifically the provision of recommendations and related user behaviour intentions. We aim to better understand to what extent users perceive career recommendations as transparent and trustworthy, and to what extent they intend to follow the provided recommendations. We examined the relationships between these variables and the role of user age. To examine these relationships, we built a model (Figure 1) following the conceptualization of transparency suggested by Schnackenberg and Tomlinson (2016) and Schnackenberg et al. (2021) and focused on clarity, accuracy, and information disclosure as key dimensions of transparency. To understand the relationships of trust and trustworthiness, followed the model of Mayer et al. (1995) and Hong and Cho (2011) looking at trustworthiness as an antecedent of behavioural intentions, as explained in the previous section.

To understand the interrelationships between transparency, trustworthiness, behavioural intentions, and user age we tested the formulated hypotheses H1–H8d (Figure 1). The results of the hypothesis testing are presented in Figure 4.

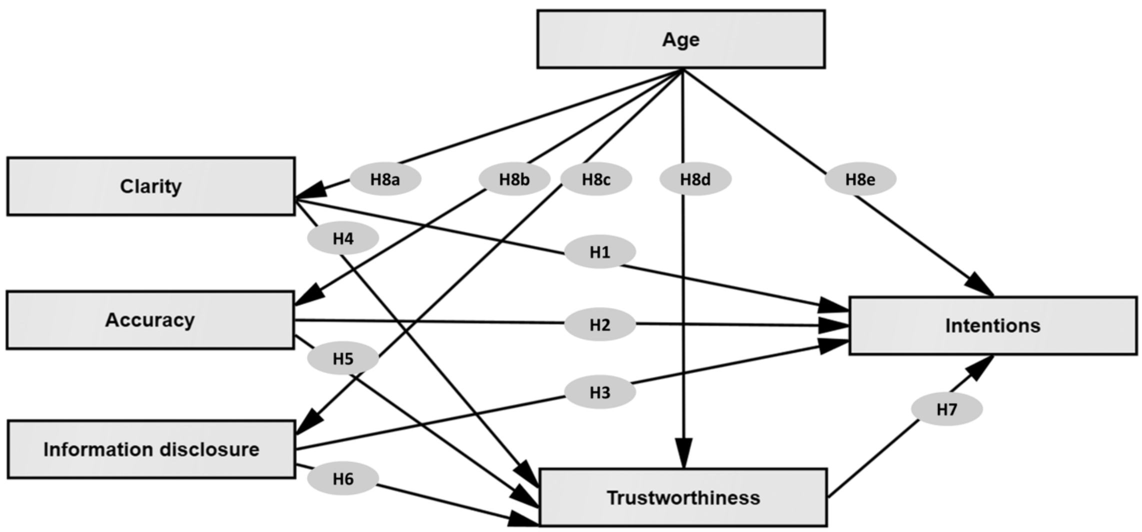


**Figure 1.** Hypothesis of interrelationships between variables.

Research Questions:

1. What are the users' views of transparency and trustworthiness, and what are their intentions to follow the recommendations of the LA career guidance tool?
2. What is the interplay among transparency, trustworthiness, and intentions to follow the recommendations of the LA career guidance tool? (Hypotheses 1–7)
3. What is the relationship of transparency, trustworthiness, and intentions to follow the recommendations with age? (Hypothesis H8)

## 2. Methods

This study utilizes data gathered during a project in Finland.[1]

### 2.1. The LA Tool for Guidance

The LA tool for guidance was a proof-of-concept designed to illustrate the possibilities of big data and educational registries in Finland for career guidance. The tool utilized mock-up data from Finnish national education registries and suggested user-relevant program choices from vocational education and training institutions or applied universities in Finland. The system was based on a tool from natural language processing (NLP), a sub-field of AI, called word embeddings (Mikolov et al., 2013) and similarity of contents. The LA tool for guidance consisted of three interlinked components: 1) prior education topics, 2) current interests and aspirations, and 3) a combination of these, resulting in recommendations of study programs and places (Figure 2). From the user perspective, the LA tool for guidance presented the user with different elements of prior education (mock-up data provided several education backgrounds to choose from) and asked the user to identify which elements they liked and disliked. On the next page, users were asked to choose their interests from a provided list grouped into 13 categories. On the final page, users received a list of recommended study programs, which could be filtered by location and institution.

[1] https://github.com/Opetushallitus/compleap

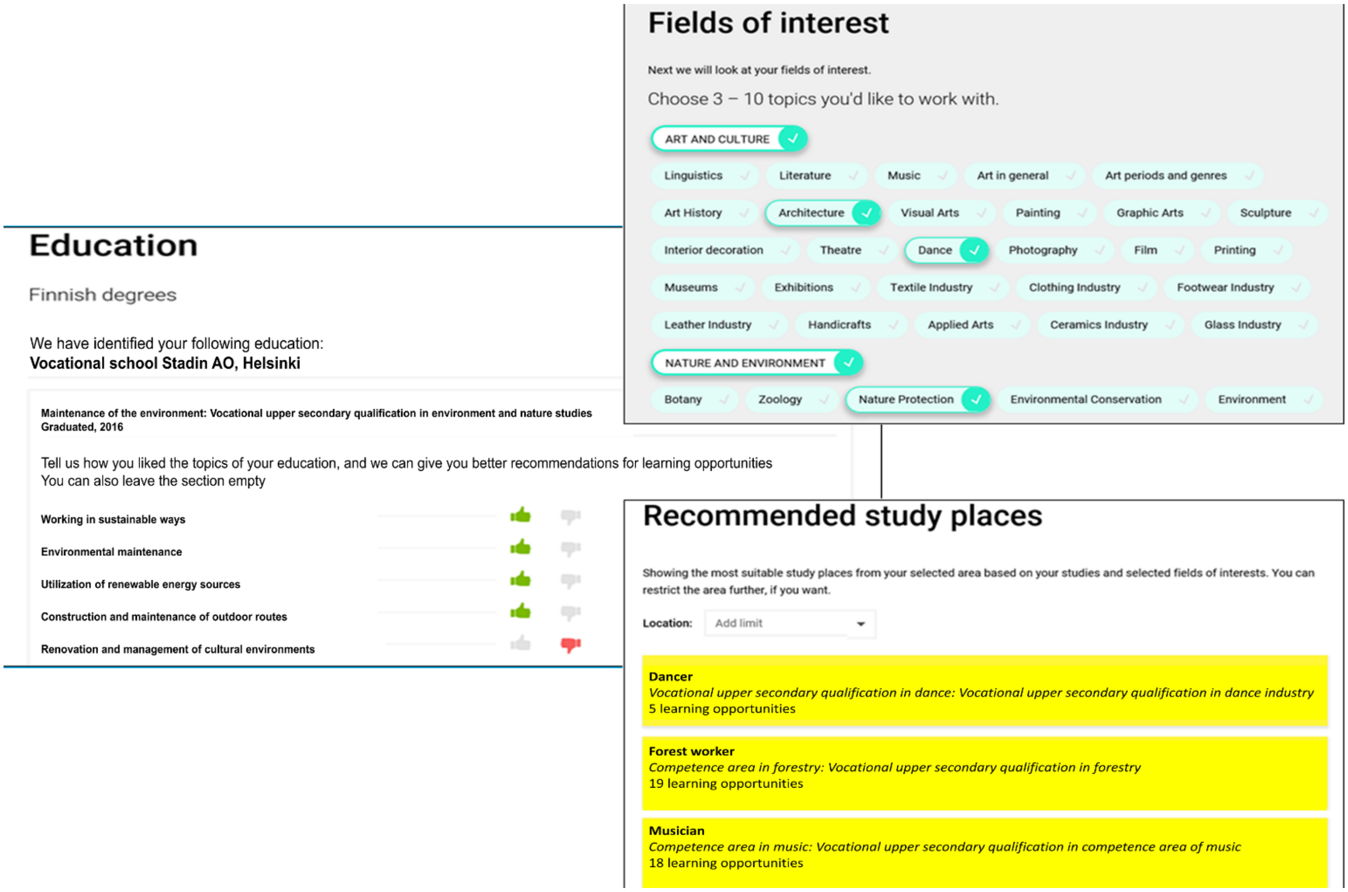


**Figure 2.** Screenshots of the three parts of the LA career guidance tool from the user perspective: previous education, current interests, and recommended study programs.

## 2.2. Participants

The participants ($N$ = 106) were real clients of the career guidance services in Finland and had varying demographic characteristics. Participants deployed the LA tool for guidance in the career counselling setting and then answered questions in an online questionnaire. An overview of demographic characteristics, means for each answer, and standard deviations (SD) are presented in Table 1. On average, participants were 21.7 years old ($SD$ = 7.8).

**Table 1.** User Demographic Characteristics and Means of Responses

| | | Mean (*SD*) | | | | |
|---|---|---|---|---|---|---|
| | *N* (%) | Clarity | Accuracy | Disclosure | Trustworthiness | Intentions |
| Overall | 106 (100%) | 3.11 (1.436) | 3.10 (1.330) | 3.21 (1.240) | 3.36 (1.429) | 3.13 (1.273) |
| Gender | | | | | | |
| Men | 45 (42%) | 3.11 (1.352) | 3.2 (1.236) | 3.29 (1.272) | 3.45 (1.284) | 3.33 (1.225) |
| Women | 60 (57%) | 3.15 (1.494) | 3.07 (1.388) | 3.15 (1.233) | 3.3 (1.544) | 2.98 (1.308) |
| Language background | | | | | | |
| Finnish | 92 (87%) | 3.12 (1.413) | 3.16 (1.328) | 3.21 (1.227) | 3.44 (1.408) | 3.27 (1.223) |
| Other language | 12 (11%) | 3.17 (1.642) | 2.27 (1.288) | 3.33 (1.303) | 3.00 (1.537) | 2.42 (1.240) |
| Preference | | | | | | |
| Digital guidance | 40 (38%) | 3.18 (1.394) | 3.02 (1.271) | 3.15 (1.231) | 3.41 (1.371) | 3.40 (1.277) |
| No preference for digital guidance | 66 (62%) | 3.08 (1.471) | 3.15 (1.373) | 3.24 (1.253) | 3.33 (3.471) | 2.97 (1.252) |

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### 2.3. Data Gathering

The first comprehensive measures of transparency as a construct were published in 2020 (Schnackenberg et al., 2021; Shin, 2020) and were not available during the data gathering period of this project. However, the user experience of transparency, trustworthiness, and trust can also be evaluated using single-item questions, as in the studies of Lee (2018) and Ribes et al. (2021). Thus, in our research, trustworthiness, trust, and transparency are evaluated by single-question items to accommodate the participants, as has been successfully done in other studies using self-reported questionnaires in the field of psychology (e.g., Dindar et al., 2020). Data was gathered using an online questionnaire about user experiences of trustworthiness, transparency, and trust of the LA career guidance tool. Evaluation was done using a 5-point Likert scale (from 1 = *completely disagree* to 5 = *completely agree*). Measured constructs, definitions, and questions are presented in Table 2. As suggested and conceptualized in previous research (Schnackenberg et al., 2021), we address transparency with three sub-dimensions: clarity, accuracy, and information disclosure.

In open-ended questions, users were asked to provide their experiences and feedback (In what situations would you use the LA tool? Could the LA tool help you apply to education or a job? Why or why not? How could you benefit from the information you got using the LA tool? What feedback could you give about the LA tool? What functionalities would you want the LA tool to have?). Answers to these open-ended questions were used to illustrate user intentions, and views on transparency and trustworthiness issues in the recommendations, and to provide a better understanding of the variables in the quantitative parts of the study.

**Table 2.** Definitions of the Measured Constructs

| Variable | Definition | Evaluation item |
|---|---|---|
| Transparency: Clarity | Users' perceived understanding of origin of the recommendations | *The basis of recommendations was clear to me* |
| Transparency: Accuracy | Users' perception of recommendation as precise and understandable | *The education opportunities recommended were fitting and made sense* |
| Transparency: Information disclosure | Users' perception of the scope of information available | *The amount of education opportunities recommended by the application was sufficient* |
| Trustworthiness | Overall users' perception of recommendations as reliable | *The recommendations felt trustworthy* |
| Intentions | Overall users' intention to follow the recommendations | *I would consider applying to the recommended study program* |

### 2.4. Data Analysis

User experiences were analyzed and presented descriptively using percentages, independent *t*-test samples, and correlation analysis. For better interpretation of the descriptive results, percentages shown in Figure 3 present answers from the 5-point Likert scale combined into three groups: negative (1 = *completely disagree* and 2 = *disagree*), neutral (3 = *not sure*), and positive (4 = *agree* and 5 = *completely agree*). Other calculations were done using the original 5-point Likert scale answers.

Qualitative content analysis (Bengtsson, 2016) was carried out on the answers, in which users provided their general views and concerns related to the LA career guidance tool. The unit of analysis was a user's unique meaningful idea or experience. The first author of this article read the answers to the open-ended questions, identified the manifested text examples relevant to the variables researched in this study, and grouped them thematically according to the definition presented in Table 2. Illustrative examples are provided in section 3.1.

To examine the relationships between variables and to test the formulated hypotheses, we conducted path analysis using Structural Equation Modelling (SEM) in AMOS 19. For all calculations of the significant path, the maximum likelihood technique was used at minimum $p \leq .05$. For the analysis of age interrelations in the SEM model, missing values in the age variable were imputed with the mean age.

## 3. Results

The first research questions focused on clarifying general user views of the LA guidance tool. Results are presented in Figure 3.

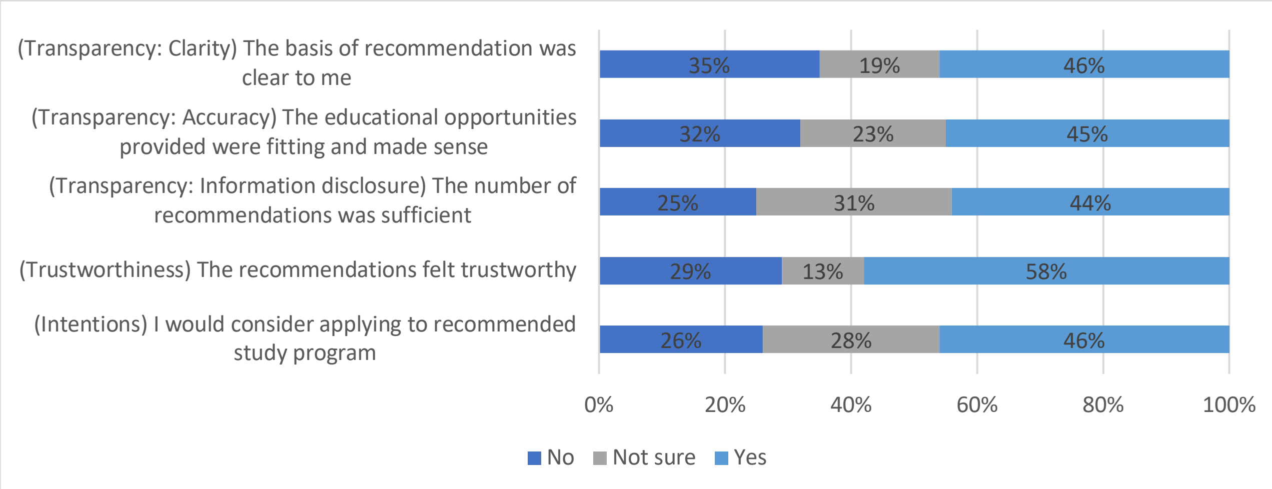


**Figure 3.** User view of the LA career guidance tool.

### 3.1. Transparency, Trustworthiness, and Intention to Follow Recommendations

Further we present examples of user views of transparency, trustworthiness, and intentions to follow the provided recommendations.

#### 3.1.1. Transparency: Clarity of the Basis of the Recommendations

Forty-six percent of users indicated that the basis of recommendation was clear to them. However, in the open sections of the questionnaire, only a small number of users commented on this issue. For example, one user wrote that *"Some of the given recommendations and the basis on which they were given raised questions"* (man, age 25, unemployed). Others were concerned about the process of eliminating certain education options in the creation of recommendations: *"[I have] some fear of what is left out of the recommendations and why"* (woman, age 36, working).

#### 3.1.2. Transparency: Accuracy

Provided recommendations were accurate for 45% of the users. The rest viewed them as either completely not fitting (32%), or they were not sure whether they made sense or not (23%). Users also commented on the accuracy of the recommendations: *"I would suggest the application to a friend and even use it myself after it is de-bugged and, for example, the suggested education places are more accurate and suggest the right options"* (man, age 18, studying).

The perceived accuracy of the tool was connected to the content of the recommended study program being in line with user interests. One 22-year-old female student said that the tool *"should provide education options that are more related to interests."* A 19-year-old male student commented that the *"logical order of recommended study locations [should] mirror selected interests."*

#### 3.1.3. Transparency: Information Disclosure

The number of recommendations was sufficient for 44% of the users. Some appreciated the novelty aspect of the recommendations and said it introduced new possibilities. One female student said that the tool *"gives a wide range of learning opportunities that you might not have thought about."* This was, however, not the experience of all users. Opposite views also emerged, such as from one 18-year-old male student, who said, *"It feels like the app does little to provide enough different options. The descriptions of the training options were quite short and superficial."*

#### 3.1.4. Trustworthiness

Almost 60% of users perceived the LA career guidance tool as trustworthy. Trustworthiness also emerged as the best evaluated aspect of the tool. Some answers indicated that users trusted the LA career guidance tool, similarly to other guidance services, and would count on it in difficult life situations. Provided recommendations were seen as an accurate reflection of reality. One 26-year-old female worker said that the tool *"could help you refine what all the options are in reality. The service could also act as your own 'personal guidance counsellor.'"* Another user, and 18-year-old male student, said *"After vocational studies, if I have any doubts about further education, or if I quit my studies at some point and I don't know where to go. The app could help me find the right place to study specifically for me."* Other answers showed that users lacked understanding of the factors influencing the trustworthiness of the results: *"When there is plenty of time to try different options in the answers — so you get more suggestions/answers — of course, then the results of the application are hardly 'reliable'"* (woman, age 50, working).

### 3.1.5. Intention to Follow

Forty-six percent of users indicated that they would consider applying to the recommended study programs. In the open-ended sections only small number of users talked about their further intentions. Some users, however, expressed opinions that showed trust in the LA career guidance tool and willingness to utilize its recommendations in the decision-making process. This sampling of answers comes from four different students:

> *"The app provides an easy way to list the right schools for you. You don't really have to decide only using your own opinions, but you get support based on your success in previous areas."* (man, age 20)
>
> *"The app tells me what I need; the app tells me what I want."* (man, age 34)
>
> *"I could apply to a school that the app suggests if it feels like my own."* (woman, age 25)
>
> *"[The tool] gives different options, based on which you can apply [to different programs]."* (woman, age 17)

## 3.2. Demographic Characteristics: Age, Gender, Language Background, and Guidance Preferences

We analyzed how users' demographic characteristics of age, gender, language background, and guidance preferences related to their perceptions of trustworthiness and transparency, and their intentions. Descriptive statistics of these variables are presented in Table 1. Results indicated no significant differences by gender, nor by their preference (or not) for digital guidance. Users who did not prefer digital guidance ($n$ = 66) had less intention to follow the provided recommendations ($M$ = 2.97) compared to those who preferred digital services ($n$ = 40; $M$ = 3.4), but the difference was not statistically significant ($t(104)$ = 1.702, $p$ = .094). No significant differences were found between users with Finnish ($n$ = 92) or other language backgrounds ($n$ = 12) in their experiences of clarity, accuracy, information disclosure, and trustworthiness. However, users with other language backgrounds were found, on average, to express weaker intentions to follow the recommended study programs ($t(102)$ = 2.274, $p$ = .025) compared to Finnish language users. Hedges's $g$ was used as an appropriate effect size measure for unequal sample sizes. Hedges's $g$ = .693, indicating a medium effect size.

A statistically significant link was found with age. As age decreased, users were more likely to state that the basis of recommendations was clear ($n$ = 95, $r$ = -.330, $p \leq .01$) and that the recommendations were accurate and meaningful for them ($n$ = 95, $r$ = -.245, $p$ = .017). They were more likely to state that the provided study options were enough for them ($N$ = 95, $r$ = -.365, $p \leq .01$) and to see the recommendations as trustworthy ($n$ = 94, $r$ = -.271, $p \leq .01$). As age deceased, users were also more likely to state that they would consider applying to the recommended study places ($n$ = 95, $r$ = -.120). However, the latter correlation was not statistically significant ($p \geq .05$).

To answer the second and third research questions, we examined the paths between the variables of transparency, trustworthiness, and intentions and tested the formulated hypotheses. The results of the path analysis are presented in Figure 4; the results of the hypothesis testing are presented in Table 3. Results indicate that out of 12 hypotheses, seven were accepted and five rejected. The accuracy dimension of transparency had a positive influence on intentions (H2, $\beta$ = .36); trustworthiness was positively influenced by clarity (H4, $\beta$ =.32) and accuracy (H5, $\beta$ = .52). Neither the clarity (H1) nor information disclosure (H3) dimensions of transparency had influence on intentions. The analysis of the influence of age on user perceptions and intentions revealed that age negatively influenced perceptions of clarity (H8a, $\beta$ = -.32), accuracy (H8b, $\beta$ = -.24), and information discourse (H8c, $\beta$ = -.35). Age had no significant influence on trustworthiness or intentions.

Together perceptions of clarity and accuracy explained 59% of the variation in perceptions of trustworthiness. Perceptions of trustworthiness and accuracy explained 40% of the variation in intentions to follow the recommendations. Some indirect influences were reported as well (Table 3). Both accuracy ($\beta$ = .10) and clarity ($\beta$ = .17) had a small positive indirect influence on intentions though perceptions of trustworthiness did not. Similarly, age had a small negative indirect effect on trustworthiness and intentions.

The goodness of fit test was used to evaluate the fit between the data and the model. Standardized $\chi$ 2/$df$ (chi-square = 1.4), which is in general regarded as a good fit. RMSEA (root mean square error of approximation = .06), NFI (normed fit index = .98), CFI (comparative fit index = .99), GFI (goodness-of-fit index = .98), AGFI (adjusted goodness of fit = .91), and TLI (Tucker-Lewis index = .98), were all within the range of acceptable values.[2] Thus, we infer that the model was well fitted to the data.

[2] For good and acceptable fit indices, please see Hu and Bentler (1999).

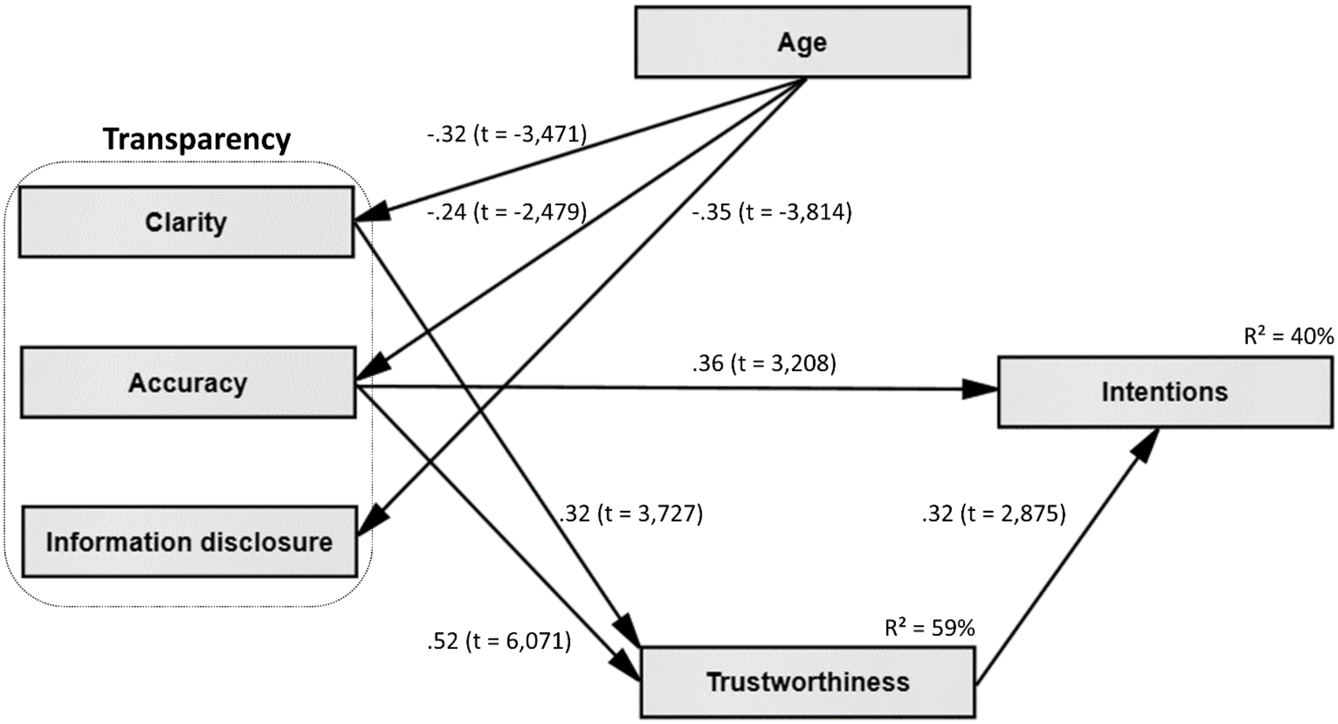


**Figure 4.** Results of path analysis.

**Table 3.** Results of Hypothesis Testing with Standardized Estimates

| H | Path | Direct effect | Indirect effect | Total effect | Standard error | *p*-value | Results |
|---|---|---|---|---|---|---|---|
| H1 | Clarity → Intentions | — | .10 | .10 | — | > 0.05 | Rejected |
| H2 | Accuracy → Intentions | .36 | .17 | .52 | .11 | .001 | Accepted |
| H3 | Disclosure → Intentions | — | — | — | — | > 0.05 | Rejected |
| H4 | Clarity → Trustworthiness | .32 | — | .32 | .09 | .000 | Accepted |
| H5 | Accuracy → Trustworthiness | .52 | — | .52 | .09 | .000 | Accepted |
| H6 | Disclosure → Trustworthiness | — | — | — | — | > 0.05 | Rejected |
| H7 | Trustworthiness → Intentions | .32 | — | .32 | .10 | .004 | Accepted |
| H8a | Age → Clarity | -.32 | — | -.32 | .02 | .000 | Accepted |
| H8b | Age → Accuracy | -.24 | — | -.24 | .02 | .013 | Accepted |
| H8c | Age → Disclosure | -.35 | — | -.35 | .02 | .000 | Accepted |
| H8d | Age → Trustworthiness | — | -.23 | -.23 | — | > 0.05 | Rejected |
| H8e | Age → Intentions | — | -.16 | -.16 | — | > 0.05 | Rejected |

*Note*: Total effect = direct effect + indirect effect.

## 4. Discussion

In this study, we examined the role of transparency and trustworthiness in user intentions to follow the LA career guidance tool recommendations. We found that users perceived these recommendations as trustworthy, but less transparent. That is, while users found the recommendations reliable, it was difficult for them to understand how such recommendations were created. This is in line with previous research showing that information and processes behind career recommendations creation remain largely inaccessible to users (Gedrimiene et al., 2023) but that trust in these recommendations is nonetheless high (Harman et al., 2014).

Our research model investigated transparency as a multidimensional construct. Among three transparency dimensions, only accuracy had a direct positive influence on user intentions to follow the LA career tool recommendations (H2). Accordingly, if users felt that the recommendations were accurate and well aligned with their interests, they were more likely to consider applying to suggested programs. The origin of the recommendations provided was not clear to many of the users, and some expressed their related concerns. However, clarity of the origins of these recommendations had no direct influence on user intentions to follow them and to apply to the suggested study places (H1). We conclude that users prioritize accuracy over clarity in using the LA career guidance tool. This lack of user concern about how the recommendations are created indicates that even in cases when the LA tool is functioning as a black box, this lack of clarity would not directly affect user behaviour. Thus, the black box phenomenon is of more concern to professionals than to users; in fact, users may follow algorithmic guidance of unclear origins.

Our study highlights the major role of accuracy in influencing user intention when engaging with AI-powered LA tools. Similarly, Ashfaq et al. (2020) suggested that more accurate information might lead to an increase in user satisfaction with emerging technologies. Likewise, Felzmann et al. (2019) considered that explanations of recommendations might not be interesting to users from the practical perspective. Consistent with previous research, our findings may be also useful in examining the transparency ideal. For instance, Ananny and Crawford (2018) analyzed transparency as the privilege of being able to see inside a system. They argued that such a transparency ideal can facilitate a false image of individual agency, as well as disconnecting transparency from meaning, understanding, and trust. Moreover, it can overlook technical and temporal limitations, and ignore the necessity of well-managed transparency that enables change (Ananny & Crawford, 2018). Accordingly, effective support for individual agency should be of primary important for the career guidance field. Consequently, different means to secure ethical, effective career guidance in the age of AI should be explored.

Both accuracy (H5) and clarity (H4) positively influenced perceived trustworthiness. Accuracy, however, played a more vital role than clarity. Thus, when the basis of recommendations was clear, and especially if they were precise and well aligned with user interests, users evaluated the recommendations as trustworthy. Trustworthiness was also the best-evaluated aspect of the tool, and some users compared it to traditional human-based guidance services. Perceptions of trustworthiness had a direct positive influence on the intention to follow the recommendations (H7). This was consistent with previous findings of Hong and Cho (2011) although in a different research context.

Both clarity and accuracy reflected the content of the recommendations, which suggests that qualitative aspects are more important to build trust in LA-based career guidance. In contrast, the information disclosure aspect, which in our study was measured by the quantitatively orientated question, was not related to trustworthiness (H6), nor to the intention to follow the recommendations (H3).

Next, our analysis revealed that age had a negative influence on all dimensions of transparency, suggesting that younger users saw the origin of the recommendations as clearer (H8a), saw the recommendations as more fitting (H8b), and were more content with the number of suggested study programs and places (H8c). Several explanations might account for this. First, younger users might be more used to digital tools and algorithmic recommendations; thus, perceived transparency might be influenced by previous experience. Second, age might be a proxy variable for more complex life experiences, needs, and expectations, thus a different quality and quantity of information and recommendations might be needed to address the complexity of older users' career decisions. Older users might also be more critical of the provided recommendations and attentive to their origins. More research is needed to investigate these possibilities and to design personalized career guidance tools for all age groups. Moreover, special attention should also be given to users with different language backgrounds, as they were shown to have weaker intentions to follow the recommendations. More research might be needed to develop suitable technology-based guidance for these user groups.

Finally, given that AI is already widely used in job recruitment (Albert, 2019; Eubanks, 2022) and knowing that predictions of education success is a growing research focus of LA (Namoun & Alshanqiti, 2020), it is only a question of time before predictions for course and program completion transfer to predictive career success rates in AI-based guidance. Such predictions should be handled with great care and with emphasis on trustworthiness, as highlighted by the European Commission (2021).

### 4.1. Implications for Practice

The study also has several implications for practice. First, developers should focus on accuracy as a key requirement in building trustworthiness and directing user behaviour intentions in LA-based career guidance. Specifically matching recommended educational content with the user's interests should be prioritized. Additionally, to develop trustworthy LA tools for guidance, more attention should be devoted to the quality rather than quantity of presented information. Second, adapting education recommendations not only to user interests but to their demographic characteristics might be considered. Specifically, as user age increased, more recommendations, more precisely fitted to their interests, and more clearly explained reasons for recommending specific programs were required. Third, we suggest that focusing on accuracy and the provision of objective accuracy indicators for users and professionals should also be more strongly emphasized, in line with recommendations from Aroyo et al. (2021), especially focusing on AI-based career guidance possibilities and limitations regarding trust.

Guidance professionals might consider our findings as a reference for choosing the most suitable guidance approach for people of diverse ages, cultures, or language backgrounds. Specifically, individual background may play a role in how clear and accurate such tools will appear to their users and how likely they will be to follow the provided recommendations. Guidance professionals might also observe if users are not overly trusting of the algorithmic guidance and take action to educate them on the possible limitations of LA-based guidance.

Finally, the field of LA could rethink the role of transparency in LA tools. Although our research shows that understanding the origin of the recommendations does not have a direct effect on user behaviour intentions, we do not claim that transparency is unimportant in developing and using LA. Lack of user understanding of and interest in the process of recommendations creation suggests the importance of legislation and responsibility of LA and other professionals to develop and utilize ethically sound and inclusive tools.

### 4.2. Significance of the Study

This study provides several contributions. First, it offers empirical evidence on the ethical concepts of transparency and trustworthiness in relation to LA use. Previous research has emphasized the importance of transparency in LA development and use; however, these accounts were limited to conceptual commentaries (Pardo & Siemens, 2014), ethical codes of conduct (Sclater, 2016; Drachsler & Greller, 2016), and reviews (Silvola et al., 2021). This is the first study, to the best of our knowledge, to empirically investigate the role of ethical considerations in the utilization of AI enhanced LA tools. Second, it expands the understanding of AI enhanced LA use by going beyond LA use in a single institution. Previous LA research emphasized LA use in higher education, leaving the perspectives of diverse groups of learners out of the picture (Viberg et al., 2018). In response to this gap, the current study focuses on use of the LA tool unbound to a specific institution. Third, the study connects LA to the topic of career guidance. LA tools so far have addressed learning processes and outcomes such as motivation, engagement, and academic performance (Silvola et al., 2021; Kew & Tasir, 2022; Karaoglan Yilmaz & Yilmaz, 2021). Unlike in previous studies, in this study we address career guidance, which might be regarded as another important contribution to LA research.

### 4.3. Limitations and Future Studies

The present research is subject to limitations. The study utilized data from 2018–2019 and was a subject to Finnish legislation on limited educational registry data use. Thus, information on the personal previous educational data of users was inaccessible and was replaced by several educational backgrounds for users to pick from. The tested LA tool was a proof-of-concept and as with all LA research cases, the tested tool had its impact on the results. For instance, the tool it might have been difficult to use for some users. Previous research indicated that the appearance of the tested tool relates to its perceived trustworthiness (Bøegh, 2014); however, it is not clear to what extent the current development level of the tested LA tool affected the results. At the same time, prototype testing is a necessary part of user-centred technology development. Future research could investigate the final version of the tool, in actual practice, with a larger sample size.

Since the research on LA transparency is still developing, the conceptualizations and measurement instruments are yet not consistent. Thus, the data collection questionnaire used in this study reflects the state of the field at the time; its limitations are discussed in the methods section. Therefore, further research is needed to deepen and solidify the evidence in the field. For instance, further research could include a systematic review of different concepts of transparency. Researchers could also investigate how dimensions of transparency interrelate with dimensions of trustworthiness (competence, benevolence, integrity), and how these could be contextualized in relation to LA and career guidance technology. Further research should also seek the preferences of users and compare AI-guided counselling with human-guided counselling. Previous research in the field of hiring, for example, has demonstrated that individuals perceived decisions by human and algorithmic recruiters differently, and that preferences varied based on the individual’s working history and needs (Fumagalli et al., 2022).

## 5. Conclusions

To summarize, it may be hard or even impossible to say how much trust users should place in career recommendations provided by LA and AI tools. First, overtrust in career guidance technology is hard to investigate empirically since information about the reliability of the technology in question is rarely presented by objective indicators. Second, real-life consequences of career and education decisions might take decades to unfold. Finally, research on overtrust in AI technologies is only starting to develop and does not yet have a strong conceptual grounding, as discussed by Aroyo et al. (2021). However, considering that the tested LA guidance tool was a proof-of-concept application with limited data sources and scope, the results raise concerns that users overestimated the extent of available information and evaluated the recommendations as more trustworthy than expected.

In their recent publication devoted to career decision-making process and AI, Gati and Kulcsár (2021) raised a question about how individuals can be encouraged to consider AI recommendations not as imposed decisions but as expert advice. We suggest that recommendations are already regarded as trustworthy expert advice, and that further work is needed to educate users about the limitations of this advice. Further focus on guidance technology is needed to assure that the direction of development is in line with the legal regulations and ethical principles of the field. This requires the active interest and collaboration of researchers, as well as career guidance professionals.

## Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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