Digitalisation: Chance or Threat for Women and Girls?

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Abstract – Digitalisation is nearly in every part of our lives and is seen as *the* promising solutions for almost any problem in the future. But what is the role of women in digitalisation? Is digitalisation a chance or rather a threat for women and girls? The current state of technology, development patterns and ICT's access perpetuate inequality for women and girls. To overcome algorithmic injustice all algorithms and development patterns have to be transparent, explained, and publicly accessible to challenge them against (gender) bias. This essay is formulated as a speech showing some consequences of the gender biases and highlighting possible actions to fight for more justice and transparency.

Key words: digitalisation, AI, women, girls, inequality, sustainability, algorithmic justice, algorithmic transparency

Introduction

Digitalisation is nearly in every part of our lives: from autonomous driving, clinical decision support systems (CDSS), automated hiring platforms, fitness apps for a healthier life to video conferencing systems – they all promise to make our lives better. Autonomous driving is supposed to make the traffic safer, CDSS is developed to make clinical decisions more evidence-based by taking more cases into account to derive a diagnosis or an appropriate treatment, video conferencing systems reduce CO_2 emissions by avoiding flights and traffic, and the automated hiring systems claim to make the application process neutral, eliminating prejudices and other bias. ICT and AI (Information and Communication Technology and Artificial Intelligence) form the core of any such systems and they both are seen as *the* promising solutions for nearly any problem in the future like reducing emissions, organising circular economy, and enhancing equality: in short for a (more) sustainable future.

So sustainability does not only mean preserving the biosphere by introducing circular economies but rather is a balance of environment, economy, and equity [1].

The UN's 17 SDGs (Sustainable Development Goals) speak to the topic and mentioning the application of ICTs to achieve these goals [4].

But to know how ICT and AI can contribute to a sustainable development one has to understand their basic ideas:

While ICT describes diverse technological tools like computers, mobile phones, or the internet in general to create, store, send, collect, and use data electronically [2, 3], AI refers to hardware or software systems that perform any kind of (autonomous) intelligent behaviours based on the environmental inputs "to achieve specific goals" [4, p. 3].

One UN goal where the use of ICT is specifically mentioned is goal 5 targeting *gender equality*. The targets of goal 5 are to stop any kind of discrimination and violence against women and girls and to use digital technologies, especially ICT, to empower women and girls to participate at every level of society, work, and decision-making [5, p. 14]. The same goes for goal 4 requiring *quality education* to "[e]nsure inclusive and equitable quality education and promote lifelong learning opportunities for all" [5, pp. 13-14]. Here ICTs shall help to provide equal education chances to all irrespective of gender, age, ethnicity, or (dis)abilities [5, pp. 13-14].

UN's SDGs are meant to be achieved by 2030 in less than a decade. However, today a gender digital divide still exists: Women and girls are objectively lacking access to ICT and independence in society. According to GSMA Association in 2021 women were "7% less likely than men to own a mobile phone" [6, p. 8] and 264 million fewer women than men accessing mobile internet in 2021 in low- and middle-income countries (LMICs) [6, p. 8]. As a consequence, they are lacking skills to use ICT. This, however, prevents women and girls from accessing and proactively using ICTs in the same way as men do and in consequence they are hindered to employ ICTs to empower themselves [6, pp. 20-25].

But the gender digital divide does not only exist in terms of accessibility and usage of ICTs but also in developing and applying AI driven systems. The behaviour of AI driven systems is based on the input data for training and on their algorithm. As the datasets for training are large and based on data collected in the past non-diverse available data in the internet this data is very likely biased [7, pp. 325-326]. The same applies to the algorithms, as they are complex and therefore represent a black box for laypeople and in some cases also for IT specialists, making it non-transparent and difficult to know exactly how the algorithm arrives at its behaviour and if it is fair [8, pp. 18-19].

The current state of technology, paths of development and use of and access to ICTs perpetuate inequality for women and girls. The setting most likely will not reduce the gender digital divide, and efforts must be made to close it in the future. This leads to the need for all algorithms and development patterns to be transparent, explained, and publicly accessible to challenge them against (gender) bias to overcome inequalities and eliminate the gender digital divide.

This essay is formulated as a speech showing some consequences of the gender biases in different areas and highlighting possible actions to fight for more justice.

Imagine women have access to ICTs.

But the gender gap in mobile ownership and mobile internet use still exists. For example, last year "131 million fewer women than men own a mobile phone" [6, p. 8]. Looking at the smartphone ownership the gap is almost 2.5 times bigger with 315 million fewer women owning a smartphone [6, p. 8]. The main cause of this gap is the affordability of these mobile handsets. Here the handset's costs or the credit costs for buying a handset are too high. This applies more for women as they only represent almost 45 percent of labour force in LMICs and about 46 percent worldwide [9]. So, they have less financial power to afford the mobile handset and additionally they do not always have "control over their own finances" [10, p. 139].

Other big barriers in access and use of ICTs are literacy and digital skills: Women more than men have difficulties in "how to use a mobile phone" [6, p. 55] and in reading and writing as women made up "almost two-thirds of all adults unable to read in 2019" [11, p. 5]. The challenges for mobile handset use as well as for mobile internet are among others wrong default settings regarding languages and not knowing how to change it or being not aware of all features like voice input. More prevalent among women are lower confidence levels in use of mobile handsets as they fear to make something wrong [12, 13].

The next barrier is about safety and security. This includes personal safety as women can be limited in their freedom of movement or unsafe ways to public ICT facilities to get access or to charge the phone [14, p. 7]. Furthermore, this barrier includes being worried that they could receive unwanted contact from strangers. They have concerns about information security meaning that for example no one else have access to data on their handset or the applications they are using on a phone they borrowed from a family member [6, p. 55, 15, p. 64].

But owning a mobile phone does not mean that women have access to mobile internet: Here they are facing the same barriers as they do regarding the ownership of mobile handsets. But the top barrier here is literacy and digital skills: That means, that female mobile phone owners might not be aware of mobile internet, or they do not know how to access it by their phone, facing reading or writing difficulties, do not have time to learn or insufficient support in learning how to access and use mobile internet [6, p. 59].

The second barrier is again the affordability: Either the mobile phone is not web-enabled if they could only afford a basic mobile phone, or they cannot afford the cost for data. In Africa for example they have to afford 18 percent of their monthly income for 1 GB of data [10, p. 139]. And this can be a higher barrier for women than men as they cannot earn money, or they have no control over it [10, p. 139]. But besides affordability in some cases the signal coverage is not appropriate [10, p. 139].

And the third barrier is about safety and security where mostly women are afraid of harmful content towards themselves or their family as women and girls facing greater risk of experiencing digital harm [16, p. 13]. And concerns about unwanted strangers contact and information security persist for mobile internet as well [6, p. 59].

Another barrier especially faced by women and girls is the lack of approval from families and societies to own and use a mobile handset and mobile internet [6, p. 59]. This goes hand in hand with the lack of education to develop literacy and digital skills as well as the freedom of movement and the safety of roads they need to use [10, p. 140].

To overcome the gender digital divide, we have to take several actions. First of all, there are several initiatives making the costs of web-enabled mobile handset and data affordable by lowering the price, offering loan products, giving the smartphones for free or help women to gain more financial power. If governments take part in these initiatives the acceptability of young women owning and using phones can be increased [13].

But there is also evidence that just providing a mobile handset to every woman does not mean that they empower themselves: they are still facing the barrier of literacy and digital skills. To tear down this barrier education of girls in digital skills as well as programs to support women in learning digital skills are needed [10, p. 150]. Regarding the latter it might be helpful to create agent networks with female agents as women might feel more comfortable talking to women. These agent networks should also be accessible for women in location and time [6, p. 50].

To address the barrier of safety and security we should invest in sensitisation through education and training to change social attitudes. Furthermore, implementing safeguards to make it easier for victims to report the harassment and last but not least implement sanctions through law and regulations so that the harassment has consequences for the offender and not only for the victims [10, p. 150].

And all these actions should incorporate the fight against discriminatory female stereotypes in societies.

Imagine women count in education.

Nowadays, science, technology, engineering, and math (STEM) are still seen as male domains in society and in education. Accordingly, the competence of women in these domains is often questioned. This affects the girl’s confidence in their own skills and their plan to make a career in these STEM fields. For example, the International Computer and Information Literacy Study (ICILS) found that under students of eighth’s grade in 21 countries girls tend to score higher in the computer-based assessment, but they tend to underestimate their actual ability [17, p. 61]. Such stereotypes and the lack of confidence foster the absence of girls in STEM education and thus lead to the lack of female role models encouraging girls to make their way into STEM and ICT fields [14, pp. 9-10].

But it is not only the lack of women in the education of STEM fields. Also, the fact “what it takes” to be a good programmer is biased in favour of men. Back in 1946 female workers were the majority in tech industry doing complex calculations for NASA’s Apollo 11 mission. But as the tech industry grows, new computers were developed, and coding skills become important. This leads to uncertainties about the skills of a good programmer. So, two psychologists were asked to develop an assessment. Doing so, they interviewed 1,400 engineers (only 200 were women) and developed a personality profile: Here good coders where describes as people who “don’t like people […] forming today’s […] stereotype of a nerdy, anti-social coder” [18]. Nevertheless, the developed personality profile favoured men in the hiring process, leading to the overrepresentation of men and the stereotype that the STEM field is a male domain and halved the amount of women in these fields from “36 percent to 18 percent today” [18].

Another source of stereotypes in education are the textbooks and learning materials: for example, the representation of female characters in texts and images in secondary English textbooks in 2018 were “44 percent in Malaysia and Indonesia, 37 percent in Bangladesh[,] and 24 percent in […] Pakistan” [11, pp. 2-3]. In a Chilean six grade science book only 6 percent of the characters were female. And in a Chinese primary school textbook the gender stereotypes are perpetuated by characterising all soldiers as male and all teachers as female. Here the problem again is that the textbook developers lack gender training, women are excluded from the development and thereby most textbook developers remain male [11, p. 3]. The nonreflective perpetuation of gender stereotypes in teaching and learning materials has serious implications on the gender identity and perceived career opportunities of boys and girls. And this can maintain the current stereotypes.

The career choices are not only poorly influenced by teaching and learning materials, but also by parents: For example, in Germany a study found that only 2 percent of the surveyed parents see their daughters in technical or craft trade occupations which is a fifth or respectively a quarter of parents which see their sons in these technical or craft trade occupations. Similar things can be seen in United Arab Emirates as the parents do not want to see their daughters in physically demanding jobs or male-dominated jobs where they have to interact a lot with men like in STEM fields [11, p. 2].

To overcome these stereotypes disadvantaging women we first have to address the teaching and learning materials and force them to draw a more diverse image of women and thereby create female role models for STEM careers. It is also important to incorporate more women into the development of textbooks [11, p. 3].

To address the stereotypes children are learning from their parents it might be helpful to provide more information about different career opportunities for their children to widen their horizons. And in combination with that the criteria for a good programmer should be renewed as the male definition from the late 1960s is outdated.

Imagine women occur in datasets and learning conditions of AI systems.

AI systems are presented as immune against prejudices, stereotypical thinking, and sympathy for people who are similar to oneself [8, p. 148, 14, p. 16]. But this is wrong. They are rather biased by making decisions according to male values and thought patterns. Thereby, they “turning human prejudices into seemingly objective facts” [14, p. 16]. This bias is introduced at various stages of the AI system development process: in data, in modelling processes, and in interpretations of the results [14, pp. 15-16].

Data for training can incorporate historical biases or certain groups like women can be underrepresented [14, p. 15]. Additionally, data for testing may have the same biases as they are often randomly selected sub-samples of the training dataset [7, p. 325]. One example is the Gender Shades work of Joy Buolamwini who is launching the Algorithmic Justice League. She found out that facial identification systems fail to recognize that a face of a dark-skinned women is present or fail to classify the face belonging to a (dark-skinned) woman by rather classifying them as a male face. The faces of white men, however, were classified correctly by the systems. The reason for this “is the lack of diversity in the training images and benchmark datasets” [19].

In the modelling process bias can be introduced by the developers own bias or lack of knowledge in the field of used data. This may result in misconceptions or poor decisions that are encoded into the algorithm of the AI system as one can see in the AI supported hiring processes (see below) [14, p. 15].

As the algorithm produces results there is another source for bias: Here, wrong decisions can be made due to misinterpretations of the results [14, p. 16] like perceiving an AI like Google’s LaMDA as sentient [20].

All these biases do not only have an impact on the current system they are incorporated in but also on future systems as they may use the same dataset, inherit the same assumptions in the model or introduce other misconceptions of the algorithmic results.

Another harmful concept in the development and use of AI system on a statistical basis is the *feedback loop*. Here the idea is that the system receives feedback about its performance and according to that it can be optimized. But the feedback can be biased as well. One example is Google Translate which uses masculine pronouns as default like “he said” because the ratio of masculine to feminine pronouns is 2:1 in the English corpora dataset. Every time the translation defaults to masculine the frequency of masculine pronouns in online texts is increased which worsens the ratio. Because the default setting is based on this ratio the system gets the feedback that use of masculine pronouns is appropriate [7, p. 325]. But if a system receives no feedback at all the errors in predictions and decisions cannot be discovered and removed [8, p. 16]. This happened in an assessment-tool named IMPACT which should score the performance of teacher in a High School in Washington D.C. to improve the performance of students at High School. The system gets the scoring of the student in the annual final exam in math as input and compares it with the scores from the year before. If several student’s scores got worse over the year the respective teacher is resigned because he or she could not improve or maintain the scores of the students – even though the year before another teacher taught them or they came from another school. But this system never gets feedback about the correctness of its decisions because the teachers are resigned and hence not covered by this assessment anymore [8, pp. 12-17].

Debiasing all stages of the development process of an AI system is vital to achieve algorithmic fairness. One aspect of debiasing is to raise the awareness of everyone included in the development process to be biased because everybody is biased by their experience and epistemology. Because if we are aware of our own biases we can reflect and overcome them. But this approach is limited by the knowledge and willingness of the persons. To expand this limit the development teams have to be diverse representing different cultures and experiences [14, p. 18].

Another aspect of debiasing is the technical part like data pre-processing. This requires a mathematical definition of fairness but until now there is no common definition of fairness. But again, the development of these algorithmic debiasing methods is prone to be biased again by overlooking correlations or perceiving fairness as a property test itself and not as a property of the use of the test. Even if a universal definition of fairness is found these again can only be used as a toolkit and not as the objective and neutral instance judging if the algorithm and the related data is unbiased [14, p. 18].

Imagine women’s working lives do count.

The working live always starts by searching and applying for a job and being hired. But as you might imagine this process is biased as well.

The intention of hiring platforms and AI supported hiring processes was to remove the dependency on relationships in the company and the sympathy of the personnel manager and thus making it more just for everybody [8, p. 148]. But in most cases they failed to do so.

For example, Amazon’s hiring algorithm favouring male applicants over female because the algorithm was trained on past job performance data with white men being classified as the best performers. But even excluding the applicant’s gender, the applications of women were refused because of words that are associated to women by the algorithm: i.e. CVs where words like “women’s” appears or because they were graduates from women-only colleges [17, p. 51, 21]. Using job performance data of high-performance employees to train the hiring algorithms is problematic if they are imbalanced. This practice will not promote diversity because applicants that differ from the high-performance profiles are less likely to be hired even if they might reach similar, equal or even better performance [17, p. 51].

Another source for bias in algorithms of hiring platforms is the definition of the desired employee which in most cases is the “clone of the best performers”. These assumptions and decisions made to get this definition are often based on subjective experiences and on standardized and data driven views on the hiring process by programmers and data scientists. Since the majority of these jobs are performed by men this can lead to a masculine-coloured definition of criteria and thereby enforce gender inequalities and lack of diversity. This again makes it difficult to break this cycle, as the workforce and the design of algorithms are mutually dependent [17, p. 51].

Another aspect where AI hiring platforms failed to introduce more justice is the fact that the platform fosters power imbalances between employers and candidates by offering different opportunities to use the platform: the candidates are forced to interact with the platform as defined by agreeing to background checks, describing themselves by predefined terms or by being restricted in the number of characters in open text fields. If the applicants do not agree to this, they will lose the opportunity to apply. In contrast the employers get new insights and information about the candidate they would not get in an non-automatic hiring process as the platform can analyse the data quickly and present the results to the employer [17, p. 51, 22, p. 62]. Here again women can be disadvantaged by the predefined description terms if they do not fit their self-report characteristics as well as by the criteria the applicants are compared with if they are based on male assumptions and male data.

Another way into employment is job advertisements but they are biased as well. Here the so-called "ad tech" technology is used where the advertisers automated the processes of "auctioning, targeting and placement of advertisements" [17, p. 45]. This automation acts against the possibility to analyse and challenge the performance of these systems towards biases by researchers. But also the advertisers themselves cannot analyse these systems anymore [17, p. 45]. And the underlying principle of these algorithms again is to find the most effective settings for targeting the advertisement for every type of vacancies [17, p. 46].

For example, LinkedIn found out that vacancies were more often shown to men than to women just because men were more active on this platform looking for new jobs. The reason therefore is that one of the categories for advertisement positioning was based on "behavioural data such as how often a user responds to messages or interacts with job postings" [17, p. 46]. But this does not take into account that women might have less time because of care responsibilities, or that men more likely apply even if they are not qualified enough [17, p. 46].

Job advertisements are not only biased by placement but also by wording. If an advertisement is mainly male-toned by including words like "'leader', 'competitive', and 'dominant'" [17, p. 48] women will less likely apply for this job as they feel that they are not asked. Since women are less likely to apply for jobs for which they perceive themselves not sufficiently qualified. But if words like "'support', 'understand' and 'interpersonal'" [17, p. 48] are used in the advertisement women are as likely as men to apply for this job [17, p. 48].

To act against these biases the characteristics used to score the applicants on hiring platforms should be revised and not based on the past best performers. This can also be a chance for more creativity and new problem-solving approaches. Additionally, the narrative of the absence of bias and prejudice in these systems should be abandoned as it is a lie. Regarding the advertisement the "ad tech" technology should not be used anymore, and the advertisement placement should be based on other factors than time spent on job seeking and more "feminine" wording should be used.

Imagine women take place in medicine.

The digitalisation and use of AI has also arrived in the field of medicine. But again, the gender biases exist here, too: in data as well as in devices and algorithms.

Regarding data: Due to complex female hormone cycles it is expensive and more complicated to include women in clinical trials for new drugs, treatment assessments, and device testing. Therefore, women are underrepresented in clinical data which is called the gender data gap. As one example among others, only 18.6 percent of the participants in an assessment of a digital biomarker for Parkinson's Disease (PD) were women. But the symptoms are different for male and female patients: men suffering more from rigidity and rapid-eye movement and women suffering more from dyskinesias and depression. This might have a (big) impact on the accurate detection of the symptoms and the prediction of the diagnosis [23, pp. 3-4]. The same applies to heart attacks, where the symptoms also differ between the sexes. As physicians are more trained on male symptoms “women [are] typically under-diagnosed for coronary artery disease” [23, p. 7]. This leads to an implicit gender bias if the algorithm is trained on diagnoses reports from clinical data [23, p. 7]. In these cases, the algorithms of the predictive systems cannot learn the diverse symptoms related to a disease. Thus, the algorithm may won’t perform well in the real world – disadvantaging women.

The underrepresentation of women in data is not only caused by the complexity of women’s bodies but also by the differences in access and use of mobile internet and digital devices resulting in imbalanced datasets regarding gender and other socioeconomic factors which “promote misrepresentations of [data] of digital biomarkers” [23, p. 4].

There are gender biases that arise from the devices themselves: For example, errors caused by sex or skin color can occur in the prediction of the arterial oxyhaemoglobin saturation measured by pulse oximetry [23, p. 3].

Another example are fitness monitors: here steps taken during domestic work are underestimated “by up to 74%” [24, p. 2] or steps are even not counted “while pushing a pram” [24, p. 2]. So, women might never be able to reach the recommended number of steps according to their apps even though they walk a lot due to domestic activities or pavements with the prams or wheelchairs.

A widely used approach for more fairness is to remove information about gender and related characteristics: But as inherent differences can occur, like a higher disease prevalence among the investigated population, it makes data even unfairer towards the underrepresented group in data. This results in the need of explicit use of sex and gender information to account for inherent differences and to ensure “the quality of the data” [23, p. 7].

In addition to a representative dataset with explicit sex and gender information the used algorithms for predictions have to be explainable. Explaining of the decisional process could help find representation bias in training data and in the derived conclusions in the algorithm. But it can also help to discover differences among the sexes and genders promoting the research in suitable preventions and treatments [23, p. 7].

Imagine women are represented properly in AI systems.

Women only appear stereotypically in AI systems. For example, virtual personal assistants (VPAs) like Alexa, Siri, or Cortana all have female voices. This perpetuates the picture of women being obedient assistants doing everything they are asked for. In contrast, digital advisors in legal, financial, or medical areas like IBM Watson are decision support systems. As they are gendered as men, this reinforces the stereotypes of men making decisions and women belong to service-oriented tasks [17, pp. 61-62, 25, p. 2].

Not only the representation of gender is biased but also the possibility to interact with theses assistants. The systems like Alexa and Siri disproportionately misunderstand women and other groups of people who do not have male voices. Because the dataset they are trained on contains mostly male voice recordings [24, p. 2, 25, p. 1]. So again, women are underrepresented in datasets.

These technologies also affect the offline part of women’s lives by upholding the stereotypes by the design of female VPAs and thereby define how women should behave. If women do not fulfil these stereotypes they can be punished by being perceived as less suitable and less hireable than men just because women showed more agency characteristics than expected. Moreover, a woman who shows her competence, her performance-orientation, her willingness to take responsibility, her autonomy, and her rationality which are all associated to men’s characteristics in addition of behaving according to women associated characteristics like “concern for others, affiliation tendencies, deference and emotional sensitivity” [26] is punished as well. According to that a survey from 2016 asking more than 30,000 employees “found that women who negotiated for promotions were 30% more likely than men to be labelled intimidating, bossy or aggressive” [26].

So, to overcome these gender bias more diverse data of voice recordings are needed including female voices and accents. And the dataset as well as the algorithm have to be assessed. In addition, the gender of assistants should be neutral or equal distributed among assistive tools and decision support tools.

To overcome the offline stereotypes incorporated into and reinforced by the online world women should connect themselves and show their competence, their performance, their skills, their autonomy, and rationality in combination with their social collaborative characteristics to counteract these stereotypes. Besides that, everybody should question him- or herself if he or she has fallen into this stereotype-trap to be able to actively counteract it.

Imagine we all take action for justice and transparency.

The lack of justice and transparency in all areas of life affecting women and other currently disadvantaged groups can leave one surprised, frustrated, angry, or hopeless. But there are actions we can take to make the digitalised future more just and transparent.

The first action we all can take is to raise awareness of bias in all stages and facets of AI systems.

The next action we can take is to make datasets more just and transparent. This can be done by reviewing existing datasets for imbalances in gender, ethnicity, and other vulnerable information and completing these datasets to remove the bias. The Data Nutrition Project has developed a dataset nutrition label to assess datasets with a standard measurement for their suitability for the intended use [27, 28].

Other research has developed a datasheet to mitigate societal bias and harms in new dataset. In analogy to datasheets in the electronics industry the datasheets for datasets contain information about "motivation, composition, collection process, recommended uses" [29, pp. 1-2] among others. To enable dataset creators to document their creation process in datasheets questions are provided to generate appropriate content [29, p. 2].

Even without using concepts like the dataset nutrition label or the datasheet data about the collection and annotation, the process should be documented and reported on a mandatory basis. These reports should also contain "geography[ical], gender, ethnicity and other demographic" [7, p. 326] statistics.

The next action to take is to raise diversity in development teams and in STEM and ICT fields in general [14, 17] by eliminating stereotypes in education and creating a more respectful environment for women working in these fields.

As bias is not reserved to the datasets we need assessments of algorithms as well. So, the next action we can take is one regarding fairness and transparency of algorithms themselves. Therefore, the concept of a datasheet might be applicable for algorithms as well. In these datasheets the developers should report their knowledge base and what assumptions and decisions they made, how they interpret the outcomes of the algorithm as well as tests they conducted to ensure functionality and fairness. By this we might be able to turn black boxes into "grey boxes" at least and promote transparency and accountability of algorithms.

And as last but not least action we have to stop the blind trust in technologies, datasets, and algorithms. We have to question every system at every stage, and we should never get tired of it.

We have to always keep in mind and remind others that the myth of an objective and neutral AI will never come true as we all are biased.

By taking all these actions we can turn the digitalisation from currently being a threat into a todays and future chance for women and all people.

So, imagine we all contribute to a more just, transparent, and accountable AI and digitalisation taking everybody into account.

What a wonderful future this would be!

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